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Corporate Failure Prediction and Financial Risk Spillover

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DEPARTAMENTO DE ECONOMÍA DE LA EMPRESA

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Abstract

In this dissertation, firstly, I investigate whether industry effects play an important role in forecasting corporate failure prediction. I hypothesize and find empirical evidence that two structural constraints of the industry are informative in the corporate failure prediction: (i) industry concentration and (ii) dependence on customers and suppliers. Secondly, I propose a new measure of tail risk spillover: the conditional coexceedance (CCX). The empirical evidence shows significant volatility and tail risk spillovers from the financial sector to many real sectors in the U.S. economy from 2001 to 2011. These spillovers increase in crisis periods. The CCX in a given sector is positively related to its amount of debt financing and negatively related to its valuation and investment. Thirdly, I examine the effect of tail risk spillover on financing circumstances of non-financial firms in 16 European countries between 2003 and 2011. Evidence shows that tail risk spillover of financial sectors is mostly driven by episodes of firms' characteristics. Besides, I aim to examine whether reserving cash is valuable for financially constrained firms in that it enables firms to mitigate tail risks transmitted from the financial sector. The empirical result has offered some evidence that cash provides important benefits to financially constrained firms in Euro-core zone and UK by reducing the tail risk spillover from distress financial sector in times of credit crunch.

Resumen

En esta tesis , en primer lugar, investigo si los efectos de la industria desempeñan un papel importante en la predicción de la predicción de fallos corporativa. Mi hipótesis y encontrar evidencia empírica de que dos restricciones estructurales de la industria son de carácter informativo en la predicción de fallos de las empresas: (i) la concentración de la industria y (ii) la dependencia de los clientes y proveedores. En segundo lugar, se propone una nueva medida de spillover riesgo de cola: la coexceedance condicional (CCX). La evidencia empírica muestra la volatilidad y de la cola significativa los efectos secundarios de riesgo del sector financiero a muchos sectores reales de la economía de los EE.UU. desde 2001 hasta 2011. Estos efectos secundarios se incrementan en los períodos de crisis. El CCX en un determinado sector se relaciona positivamente con la cantidad de financiación de la deuda y negativamente relacionado con su valoración y la inversión. En tercer lugar, se examina el efecto de spillover riesgo de cola sobre la financiación de las circunstancias de las empresas no financieras en 16 países europeos entre 2003 y 2011. La evidencia muestra que desborde el riesgo de cola de los sectores financieros se debe principalmente a los episodios de características de las empresas. Además, mi objetivo es examinar si la reserva de dinero en efectivo es valioso para las empresas restringidas financieramente, ya que permite a las empresas para mitigar los riesgos de cola de transmisión del sector financiero. El resultado empírico ha ofrecido algunas pruebas de que el efectivo proporciona importantes beneficios a restricciones financieras las empresas de la zona euro-core y el Reino Unido mediante la reducción de la propagación del riesgo de cola de sector financiero de socorro en tiempos de crisis crediticia.

Content

CHAPTER 1

Introduction

In this dissertation, there are three individual papers. In first article, we investigate whether structural constraints of industry will help corporate failure prediction. In second article, we propose a new measure of tail risk spillover, which named as conditional coexceedance (CCX). In third article, we aim to examine whether reserving cash is valuable for financially constrained firms in that it enables firms to mitigate tail risks transmitted from the financial sector.

The chapter 2 in the dissertation is entitled "Do Structural Constraints of the Industry Matter for Corporate Failure Prediction?". Industry effects play an important role in forecasting bankruptcy; however the actual channels of the influence of industry characteristics on failure and bankruptcy likelihood have been barely addressed in the extant literature. We hypothesize and find empirical evidence that two structural constraints of the industry are informative in the corporate failure prediction: (i) industry concentration and (ii) dependence on customers and suppliers. Using an extensive database on corporate failures and bankruptcies in the U.S. market from 1998 to 2009, we find that the probabilities of failure and bankruptcy are significantly higher for firms in highly concentrated industries. The probability of bankruptcy is higher for firms in industries with stronger customer dependency but this factor does not affect failure probabilities.

The chapter 3 in the dissertation is entitled "Industry characteristics and financial risk spillovers". This article proposes a new measure of tail risk spillover: the conditional coexceedance (CCX), defined as the number of joint occurrences of extreme negative returns in an industry, conditional on an extreme negative return in the financial sector. The empirical application provides evidence of significant volatility and tail risk spillovers from the financial sector to many real sectors in the U.S. economy from 2001 to 2011. These spillovers increase in crisis periods. The CCX in a given sector is positively related to its amount of debt financing and negatively related to its valuation and investment. Therefore, real economy sectors—which require relatively high debt financing and whose value and investment activity are relatively lower—are prime candidates for stock price volatility and depreciation in the wake of a financial sector crisis. Evidence also suggests that the higher the industry's degree of competition, the stronger the tail risk spillover from the financial sector.

The chapter 4 in the dissertation is entitled “Do Cash Holdings Influence Financial Risk Spillover? Firm Level Analysis in Europe”. This paper investigates the effect of tail risk spillovers from the financial sector to the real economy on the financing characteristics of 4320 non-financial firms located in 16 European countries from 2003 to 2011. We find that firms with negative cash holdings, low stock returns, low valuations and small distance to default suffer stronger risk spillovers. Also, the bigger the firms’ size and the higher its volatility and leverage the stronger the impact of tail risk spillovers. We find stronger tail risk spillovers for Euro-periphery countries than for Euro-core countries. These spillovers are weakest in the case of the UK Firms with relatively higher cash holdings are less exposed to tail risks originated in the financial sector.

CHAPTER 2

Do Structural Constraints of the Industry Matter for Corporate Failure Prediction?

2.1. Introduction

Industry structural constraints should affect firms' operating strategies, financial structure decisions, and profitability, and therefore their failure and bankruptcy likelihood. It is important to define the difference between failure (the broader category) and bankruptcy (the narrower category). We consider that a firm fails when its stock is removed from the exchange on which it trades due to poor performance or other reasons.[1] Companies that are delisted are not necessarily bankrupt, and may continue trading over the counter. In the USA a firm is bankrupt when it is delisted because of Chapter 7, Chapter 11, or liquidation. Therefore all bankrupt firms are included in the failure category but not all failed firms go bankrupt. The literature has documented the importance of some industry effects on bankruptcy prediction but there is scarce evidence on the impact of these factors on failure. Chava and Jarrow (2004) provide empirical evidence of the impact of industry effects in forecasting bankruptcy, but as far as we know, the actual channels of influence of industry characteristics on failure and bankruptcy likelihood have not been addressed.[2] As a first step to fill this gap in the literature we study the impact on firms' failure and bankruptcy of two specific structural constraints: (1) the intensity of industry concentration, and (2) the degree of dependence on customers and suppliers. We first hypothesize that the higher the degree of industry concentration the higher the failure and bankruptcy risks for firms in this industry. The reasons are that within concentrated industries, firms have lower profitability because they suffer more acute agency problems, see Giroud and Muller (2010), Bloom and van Reenen (2007), and Nichell (1996), and become more leveraged (Chevalier, 1995). Both elements increase the probability of financial distress and eventually the probability of failures and bankruptcies. We next hypothesize that the higher the degree of industry's customers' dependence the higher the failure and bankruptcy risks for firms in this industry. The reasons are that high customers' dependence in a given industry implies that firms in that industry tend to present poor economic performance,[3] due to the direct constraint coming from customers' market power. Our hypotheses highlight the risks inherent in low

[1] The reasons for delisting include violating regulations and/or failing to meet financial specifications set out by the stock exchange.
[2] Previous papers include dummy variables into bankruptcy prediction models to take into account different industries. Therefore their results only imply that different industries may have different bankruptcy probabilities. What is missing is the specific industrial constraint (e.g. concentration) effect.
[3] See Burt (1983), Talmud (1994), Yasuda (2005), and Burt (2008).

flexibility, whether in the kind of product offered to the market (i.e., concentrated industries tend to produce specialized products) or the customers served.

To measure industry-level variables we include macroeconomic information. Our failure and bankruptcy forecasting models also includes the standard market- and accounting-driven predictors. To assess the effect of the industry's structural constraints on failure and bankruptcy predictions, we consider corporate failures and bankruptcies by U.S. public companies during the period from 1998 to 2009.

We contribute to the literature with four main results. First, we document that failure and bankruptcy probabilities increase when the degree of competition in a given industry decreases. This result is robust to alternative industry concentration measures.[4] Also in the case of failures the degree of fit is noticeably higher (32%) than in the case of bankruptcies (20%). This fact suggests that in the decision to go bankrupt other variables may be important besides the standard controls measuring economic performance. These variables are more successful in predicting failure (delisting). Second, firms in industries that depend more on customers have higher bankruptcy probabilities than firms in industries with lower dependency levels. However this factor does not affect failure probabilities. Third, firms in industries that depend more on suppliers have lower bankruptcy probabilities than firms in industries with lower dependency levels. However this factor increases failure probabilities. Fourth, we find that the relative size, which has usually been regarded as a strong factor of explaining bankruptcy in the extant literature become relatively less important during the more recent period.[5]

The rest of this article is organized as follows: In Section 2, we relate relevant literature to our hypotheses about the effect of industry structural constraints, and Section 3 introduces the measures of industry-level variables. Section 4 describes the data. Section 5 contains the failure and bankruptcy prediction models, and Section 6 presents the main empirical results. Section 7 provides robustness tests. We conclude in Section 8.

[4] We use the Census concentration information from Bureau Economic Analysis. In addition, our robustness tests are based on (1) the *Assets-based Herfindahl Index*, and (2) *Sales-based HHI on **n**-digit Industry Code*. We also use *Eight-firm, Twenty-firm, and Fifty-firm Concentration Ratio* as alternative Census-based concentration measures.

[5] The data set used in Chava and Jarrow's (2004) and Campbell et al. (2008) is between 1962 and 1999, whereas we use data from 1998 to 2009.

2.2. Relevant Literature and Hypotheses

This paper relates firms' failure and bankruptcy probabilities to two industrial characteristics: (1) industry concentration and (2) industry customers' and suppliers' dependence on other sectors. Accordingly, three hypotheses are proposed in the following sections.

2.2.1. Product Market Concentration

Industrial organization literature suggests the structure of product markets affects managers' operating decisions that eventually determine a corporation's survivability (Brander and Lewis, 1986). Managerial incentives support that managers of firms in competitive industries are under pressure to reduce slack and improve efficiency (Giroud and Muller, 2010),[6] and poor management practices are more prevalent in non-competitive industries (Bloom and van Reenen, 2007). Chevalier (1995) claims that a decrease in the level of industry competition rises up leverage in the participating firms. Opler and Titman (1994) argue that customers are more reluctant to purchase specialized products that are likely to be produced in concentrated industries from a distressed firm.

Overall, firms in a concentrated industry are more likely to face distress due to two reasons: (1) they are less profitable because of poor management and (2) they are more leveraged. We hypothesize in turn that:

Hypothesis 1: The higher an industry's concentration, the higher the incidence of failure and bankruptcy among firms belonging to the industry.

2.2.2. External Industry Constraints

Hertzel et al. (2008) argue that a firm's financial distress is connected to firms' interaction occurred in other industries. Extant literature also suggests that both excessive dependence on customers and suppliers may negatively affect the firm's economic performance (Burt, 1983, 1988, Talmud, 1994, Yasuda, 2005, and

[6] Their results show that the corporations' operating performance for firms in competitive industries has no significant impact, while it significantly drops for those in non-competitive industries after the policy of business combination laws, which aims at reducing the threat of a hostile takeover.

Burt, 2008). However the influence of supplier dependence on firms' distress probabilities might be in opposite direction for two reasons: (1) a suppliers' dependent firm usually finds it rather easy to look for substitute suppliers; (2) a firm limits leverage both before and after contracting due to worries about suppliers threatening to curtail its specialized factors of production (Sarig 1998). We then posit the following hypotheses.

Hypothesis 2a: The stronger the direct customers' dependence, the higher the incidence of failure and bankruptcy.

Hypothesis 2b: The relationship between the direct suppliers' dependence and the incidence of failure and bankruptcy is unclear.

This paper further explores external industry effects on firms' distress associated with indirect customers' (suppliers') dependence. Burt (2008) suggest that industry-structure effect on industry performance can be related to both the industry's own buying and selling and to networks around the industry's suppliers and customers. That is to say, dependent relations embedded among the network around suppliers or customers also have potential impact on firms' distress. Here we regard this sort of dependence as indirect external dependence. Similarly to the discussion of direct external constraints, we separately consider indirect customers' constraint and indirect suppliers' constraint.

Hypothesis 3a: The stronger the indirect customers' constraints, the higher the incidence of failures and bankruptcy among firms belonging to the industry.

Hypothesis 3b: The relationship between the indirect suppliers' constraints and the incidence of bankruptcy or failures among the firms belonging to the industry is unclear.

2.3. Measures of Industry Structural Constraints

2.3.1. Concentration Ratio

We hypothesize that firms in a more concentrated industries are more likely to fail due to poor management or extreme leverage. Testing the hypothesis requires measures for evaluating the degree of industry concentration. This study tests several variables which measure industry concentration. The baseline analysis is based on the use of the Herfindahl-Hirschman index (HHI), which generates the concentration ratio in industry *j* as follows:

$$\text{Herfindahl}_j = \sum_{i=1}^{I} s_{ij}^2 \tag{1}$$

where s_{ij} is the market share of firm *i* in industry *j*. Small values of this ratio imply that the market contains many competing firms; large values imply that few large firms dominate the market. We use the entire distribution of industry market share information to assess HHI for each year and for each industry. Following Hou and Robinson (2006), we compute HHI by the use of "sales" variable provided by COMPUSTAT, denoted as sales-based HHI. The assets-based HHI, which is computed by total assets in COMPUSTAT, is also considered for robustness (see Section 2.7) purposes. Notice that we denote the COMPUSTAT concentration ratio to refer measures based on COMPUSTAT data in order to discriminate it from the Census concentration ratio which are also employed in the robustness test section.

2.3.2. External Industry Constraint

2.3.2.1. Direct Customers' and Suppliers' dependence

We are interested in resource dependence, or the extent to which producers in a given market depend on another market to buy or sell, directly or indirectly as in Burt et al. (2002). The rationale is in line with Preffer and Salancik (1978) in the sense that the dependence is defined as the importance of a given input or output to the organization and the extent to which these factors are controlled by relative few counterparties. Burt et al. (2002) measure external industry constraints by one variable that aggregate customers and suppliers together. We think it is better to analyze their effects separately and following Shih's (2007) suggestion, we split Burt et al.'s (2002) combined measure into customers' and suppliers' dependence, denoted as $C_{i,C}$ and $C_{i,S}$ respectively. For industry i, they can be calculated using the following method:

$$C_{i,type} = \sum_j c_{ij,type} \text{ , } i \neq j \text{ , } type\ C\ or\ S, \tag{2}$$

where
$$c_{ij,type} = w_{ij,type} \cdot H_j \text{ ,} \tag{3}$$

$$w_{ij,type} = \left(p_{ij,type} + \sum_q p_{iq,type} \cdot p_{qj,type} \right)^2 \text{ , } i \neq q \neq j \tag{4}$$

$$p_{ij,C} = \frac{z_{ij}}{\sum_j z_{ij}} \text{ , } p_{ij,S} = \frac{z_{ji}}{\sum_j z_{ji}} \text{ , } p_{iq,C} = \frac{z_{iq}}{\sum_j z_{ij}} \text{; and } p_{iq,S} = \frac{z_{qi}}{\sum_j z_{ji}} \text{ , } i \neq j \tag{5}$$

H_j is the concentration ratio of industry j, computed by HHI ; and z_{ij} is the dollar worth of the commodities sold to industry j from industry i. The intuition is that the squared term in Equation (4) is the degree of direct and indirect dependence of industry i on market j, measured by p_{ij}, or the proportion of industry i's sales that occur directly to market j, plus the proportion of industry i's sales that indirectly involve market j through market q. The customer (supplier) constraint on industry i is a weighted sum of dependence on customer (supplier) industries j where business is concentrated in a few dominant companies, measured by H_j. The constraint index in Eq. (2) is the sum of such dependencies, measuring the aggregate extent to which the producer is dependent on coordinated customers, as the customer constraint ($C_{i,C}$) or on coordinated suppliers, as the supplier constraint ($C_{i,S}$). It leads the notion that the larger values of $C_{i,C}$ and $C_{i,S}$ the higher dependence and consistent with arguments in Section 2, the higher external industry constraints.

2.3.2.2.Indirect Customers' and Suppliers' dependence

By definition, the indirect customers' (suppliers') dependence are captured by taking average values of direct customers' (suppliers') dependence ($C_{i,C}$ and $C_{i,S}$, see Section 3.2.1.) of other industries around the network beyond direct customers and suppliers. For a simple case, assume that industry X is trading with two industries Y and Z with $C_{i,C}$ equivalent to 13 and 14 respectively.

The indirect customers' dependence for the industry X is the average of the constraints in the industries Y and Z, which is $(13+14)/2=13.5$. The general formula is $\frac{1}{N}\sum_{n=1}^{N} C_{n,c}$, where N is the number of trading industries. Indirect suppliers' dependence is measured similarly but replacing $C_{i,C}$ by $C_{i,S}$.

2.4. Data

2.4.1. Databases

The empirical analysis is based on the data covering all firms traded on the three major U.S. exchanges (NYSE/AMEX/NASDAQ) from 1998 to 2009. To compute the degree of industrial customers' and suppliers' dependence, we use the Annual Input-Output tables with level of aggregation *Sector* published by the Bureau of Economic Analysis (BEA). Specifically, we adopt the Use Table of Input-Output Accounts for the U.S. Economy, which reports a matrix with the values of commodity flows between each pair of industries. The most updated information of Use Table is based on annual data and starts in 1998.[7] The Input–Output tables classify the industries based on the Input–Output (IO) industry code. We use the document relating North American Industry Classification System (NAICS) codes to IO codes,[8] to group firms in the CRSP/COMPUSTAT database into different industries based on IO code. If firms are not classified into one of IO codes, these observations are deleted. We end up with fourteen industries.[9]

In addition, several well-known predictors of firms' financial distress are also taken into account as control variables in the failure and bankruptcy prediction models. Following Shumway (2001) and Campbell et al. (2008), we choose six variables which are based on stock market and accounting information: (1) the annual excess return (*EXRET*), (2) the relative size (*RSIZ*), (3) the volatility (*SIGMA*), (4) the ratio of net income to total assets (*NI/TA*), (5) the ratio of total liability to total assets (*TL/TA*), and (6) the ratio of cash to

[7] We do not use Input-Output tables before 1998 because they are published every five years, such as 1987, 1992, and 1997 and do not contain yearly data

[8] This document, available on the BEA website, is "A Document for 2002 Benchmark Input-Output Accounts: Summary Make Table and Use Table before Redefinitions."

[9] The fourteen industries are : (1) agriculture, forestry; fishing and hunting; (2) mining; (3) utilities; (4) construction; (5) manufacturing; (6) wholesale trade; (7) retail trade; (8) transportation and warehousing; (9) information; (10) finance, insurance, real estate, rental, and leasing; (11) professional and business services; (12) educational services, health care, and social assistance; (13) arts, entertainment, recreation, accommodation, and food services; and (14) other services, except government.

total assets (*CASH/TA*). [10] The variables are computed by merging accounting information from COMPUSTAT (yearly, firm-level) and market information from the Center for Research in Security Prices (CRSP) (monthly, firm-level). A firm contributes a year-observation after it starts appearing in the databases until the end of the sample period or its delisting year. Following Dichev (1998), we use exchange delisting for bankruptcy or liquidation as a proxy for bankruptcy (delisting codes: 400, 572, 574), and adopt a broader measure of failure that includes firms delisted due to bankruptcy, liquidation, or poor performance (delisting codes: 400, 550－585).[11] We use June, 30 as "end-of-year" as suggested by Chava and Purnanandam (2010). That is, for every June 30 of each year, we regard a firm as failed or bankrupt if the firm is delisted during the next year (July 1 to June 30 of next year) and if its delisting code satisfies the above definition.[12] We lag accounting data by six months to ensure that it is available as of the model estimation date. For example, if a firm's fiscal year ends in December 2007, we consider this information available as of June 30, 2008. Like most of early works did (Shumway, 2001, Chava and Jarrow, 2004, Campbell et al., 2008), we discard outliers (e.g., typos, reporting errors) by truncating all variables at the 1st and 99th percentiles of their pooled distributions across all firm-year observation, and replacing any observation below the 1st percentile with the 1st percentile and any observation above the 99th percentile with the 99th percentile. This procedure (winsorizing) ensures that extreme outliers do not drive the empirical results. Finally, our sample contains 12031 firms and 72945 firm-year observations from 1998 to 2009, which includes 247 bankruptcies and 2496 failures according to these criteria.[13]

2.4.2. Description of Bankruptcies and Failures

Figure 1 depicts bankruptcies and failures as a percentage of active companies per year in our sample. The general shape of the occurrence of bankruptcies (black line) and failures (dotted line) reflects national recessions, as defined by the National Bureau of Economic Research (NBER),[14] which has reported two

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[10] The detailed information is provided in Appendix A.
[11] The Appendix B provides definitions of the CRSP delisting codes.
[12] We found that the number of bankruptcies from January to June is significantly lower than from July to December. Since yearly accounting reports are normally published several months after the end of December, firms that file for bankruptcy from January to June are very likely those firms that do not provide accounting reports for the last year. Moreover we deleted those observations which have missing data in year t-1.
[13] Note that the starting year of our independent variable in our bankruptcy prediction model is 1997 because it relies on one-year ahead data.
[14] The NBER defines a recession as "a significant decline in economic activity spread across the economy, lasting more

recessions since 1998. The first recession in the early 2000s, combined the collapse of the speculative dot-com bubble and the September 11 attacks. In Figure 1, we do find a relatively higher bankruptcy incidence in 2000–2002. The second recession called "Great Recession", running from December 2007 to June 2009. Again, in Figure 1, we observe a big increase in bankruptcies as well as failures in 2008. Overall, the failure indicator tracks the bankruptcy indicator closely except for the year 1998, when the former reached to the highest level whereas the latter was at normal level. This finding is consistent with Campbell et al. (2008) regarding the dramatic increase in failures after 1998, reflecting the financial distress of many young firms that were freshly listed during the bonanza of the late 1990s.[15]

[INSERT FIGURE 1 HERE]

Figure 2 shows bankruptcies by stock exchange listing. Over a half of the firms in our sample that filed for bankruptcy were listed on NASDAQ. The remaining percentage is almost evenly spread between the NYSE and AMEX. As for failures, almost 80% of them were listed on NASDAQ.[16]

[INSERT FIGURE 2 HERE]

Table 1 contains an overview of bankruptcies and failures by IO code. Most of them happen in the manufacturing sector (96 and 965 respectively), followed by the information industry (33 and 408) and then finance, insurance, real estate, rental, and leasing (31 and 311) during our sample period.

[INSERT TABLE 1 HERE]

2.4.3. Summary Statistics of the Independent Variables

We report summary statistics for all firms in Panel A of Table 2, and for subsamples with bankrupt and failed firms in Panels B, and C respectively.

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than a few months, normally visible in real gross domestic product (GDP), real income, employment, industrial production, and wholesale-retail sales."

[15] The bankruptcy data used in Campbell et al. (2008) is the same as the data used in Chava and Jarrow (2004). Although we only rely on delisting codes to discriminate bankruptcies and failures from other delisting firms due to other reasons, our data reflects important findings as Campbell et al. (2008) and macroeconomic situations.

[16] Shumway (2001) considers the NYSE and AMEX, where bankruptcies happen with much lower frequency than in the NASDAQ.

Economic intuition suggests that firms about to fail or file for bankruptcy should have lower than average excess returns (*EXRET*), should be relatively smaller (*RSIZ*), should be more volatile (*SIGMA*), should have lower income (*NI/TA*), large liabilities (*TL/TA*), and low liquidity (*CASH/TA*), in comparison with the aggregated sample. The summary statistics are consistent with the intuition. For example the average value of *EXRET* from the whole sample is +5% per year, whereas it is -58% and -40% in the bankruptcy and failure group respectively, which reflects the underperformance of stocks before delisting due to bankruptcy or poor performance. The overall relative size (*RSIZ*) is around -11, and it decreases to -12 and -13 for bankruptcies and failures, indicating smaller firms are more prone to financial distress. The average value of the annualized firm-level volatility (*SIGMA*) is around 48% for the whole sample, but almost doubles both in bankruptcies and failures as expected. The net income relative to total asset (*NI/TA*) is -4,7% in the whole sample, which indicates that, on average, firms suffered losses during this period. This variable is much more negative for failures (-33,8%) and bankruptcies (-22,8%). The ratio of *TL/TA* is close to 50% for all firms, and, not surprisingly, it is higher for bankruptcies and failures (75% and 64% respectively) suggesting that high leverage tends to go hand in hand with financial distress. Interestingly the cash ratio for all firms and for failed firms is similar (18%) but is somewhat lower for bankrupt firms (12%).

[INSERT TABLE 2 HERE]

The column 7 of Table 2 shows that the average concentration ratio (*HHI*) is similar in the case of bankruptcy (38%) and failure (34%), and lower for the total sample (28%). Therefore failed (bankrupt) firms tend to be in industries which are 10 (6) percentage points more concentrated than the average industry. The external industry variables (direct dependence: $C_{i,C}$, $C_{i,S}$ and indirect dependence: $IC_{i,C}$, $IC_{i,S}$), present similar values in the three panels. Table 3 contains the correlation matrix of the independent variables which shows the relatively low cross correlations among explanatory variables with the exception of $IC_{i,C}$, and $IC_{i,S}$ (0,667).

[INSERT TABLE 3 HERE]

2.5. Bankruptcy Prediction Model

Following Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008), we use a simple hazard model to estimate the probabilities of failure and bankruptcy over the next period in a dynamic logit model. The main advantage of a simple hazard model is that we can control for and adjust the firm's at-risk period. For longer sampling periods, it is important to acknowledge that some firms file for bankruptcy after many years of being at risk, whereas other firms fail in their first risky year. Our model incorporates time-varying covariates that change over time; if a firm's financial health deteriorates before failure and bankruptcy, its financial data reveals its changing financial health over time.

We assume that the marginal probability of failure and bankruptcy in the next period follows a logistic distribution, expressed as:

$$P_{t-1}\left(Y_{it}=1\right)=\frac{1}{1+\exp(-\alpha-\beta X_{i,t-1})} \tag{6}$$

with the parameters (α, β) and time-varying covariates $X_{i,t-1}$ for the discrete time hazard rate. The dependent variable Y_{it} equals to 1 when a bankruptcy or a failure takes place, and otherwise is 0.

We report McFadden's pseudo-R^2 coefficient to assess the explanatory power of a dynamic logit model, which is calculated as $1 - L_1/L_0$, where L_1 is the log-likelihood of the estimated model and L_0 is the log-likelihood of a null model consisting of only a constant term. In addition, we implement log-likelihood ratio test on the difference of -2Log(LF)[17] values between the benchmark model (only with six market- and accounting-driven variables) and models which include additionally industry-level variables. The test statistics is based on Chi-Square distribution with n degrees of freedom, where n is the difference of the number of independent variables between the two compared models.

2.6. Empirical Results

This section provides empirical evidence on the effects of industry structure on bankruptcy and failure. The analysis is based on fitting model (6) to our data set, regressing the bankruptcy or failure indicator on

[17] The -2Log(LF) denotes -2 times log likelihood value in the paper.

industry constraint variables (*HHI*, $C_{i,C}$, $C_{i,S}$, $IC_{i,C}$, $IC_{i,S}$) and market- and accounting-driven variables as additional controls.

2.6.1. The Impact of Industry Constraints on Bankruptcies

The results are in Table 4. The baseline specification including only the six controls is the Model 1. All variables, except *NI/TA*, are significant at conventional levels and present the expected signs. That is, increases in *EXERT* and *RSIZ*, *NI/TA*, *CASH/TA* reduce the probability of bankruptcy, whereas increases in *SIGMA* and *TL/TA* have the opposite effect. Consistently with Chava and Jarrow's (2004) we find that *NI/TA* is not significant when including market-driven variables in the bankruptcy model. The variable *RSIZ*, is only marginally significant in the Model 1 and becomes non-significant when the concentration and direct industry constraints variables are added into models (see Model 2 and 3). This finding deserves two comments. First, the relative size has usually been regarded as a strong factor of bankruptcy in the literature, whereas our results suggest a diminishing impact when using a more recent data set. Second, the significance of *RSIZ* vanishes once industry constraint variables are added into the bankruptcy model. This fact implies that the industry structural effect dominates the effect of firms' relative size on predicting bankruptcy in this sample.

[INSERT TABLE 4 HERE]

The Models 2, 3, and 4 are designed to test whether industry structural constraints provide extra predicting power upon the traditional bankruptcy prediction model. First, the measure of industry concentration *HHI* is always significantly positive across all regressions. This is consistent with the first hypothesis, namely, that the higher the industry concentration level, the higher the bankruptcy probability. Panel B shows that the difference of -2Log(LF) between the Model 1 and the Model 2 is 21,12, and the near zero p-value[18] implies that the intensity of industry concentration gives extra power in discriminating bankrupt entities from non-bankrupt ones.

[18] P-VALUE is computed from chi-square distribution with *n* degree of freedom, where *n* refers to the difference of the number of independent variables between two compared models.

Second, the estimation results of Model 3 show a significantly positive impact of the direct customer constraint ($C_{i,C}$), and a significantly negative impact of the direct supplier constraint ($C_{i,S}$). The former finding suggest that the stronger customers' dependence the higher the probability of bankruptcy, which is consistent with the *hypothesis 2a*. The latter finding supports the concept in Sarig (1998) that when a firm worries about suppliers threatening to curtail its specialized factors of production, it reacts limiting its leverage and thus reducing the firms' probability of bankruptcy. The implication is that the sign in *hypothesis 2b* should be negative. The difference of -2Log(LF) values between the Model 1 and the Model 3 is 38,58, and the near zero p-value indicates that direct external industry constraints provide additional power on bankruptcy prediction.

Finally, the Model 4 shows that the effect of $IC_{i,C}$ is significantly positive, whereas the effect of $IC_{i,S}$ is negative and marginally significant. The former result indicates that firms are more likely to go bankrupt when operating in an industry with high-level customer dependence around the network of other industries, which is consistent with the *hypothesis 3a*. The difference of -2Log(LF) values between Model 1 and Model 4 is 48,8 with p-value close to 0, which again suggests that industry structural constraints do matter for bankruptcy prediction although their economic impact is not striking.

2.6.2. The Impact of Industry Constraints on Failures

The estimation results are reported in Table 5. First, variables on the benchmark model (the Model 1) are all consistent with expected signs and strongly significant. Compared to our previous results on the case of bankruptcies, failures appear more often to firms with smaller size and lower net income. Also the degree of fit is noticeably higher (32%) than in the case of bankruptcies (20%). This fact suggests that in the decision to go bankrupt other variables may be important besides the standard controls measuring economic performance. These variables are more successful in predicting failure (delisting). Second, the impact of *HHI* is always significantly positive, which once again backs up the Hypothesis 1. Third, the variables $C_{i,C}$ and $C_{i,S}$ are not significant (Model 3). When included in Model 4 $C_{i,S}$ is positive (in contradiction with the results for bankruptcies) and significant. The effect of $IC_{i,C}$ is negative and significant and the effect of $IC_{i,S}$ is positive and significant. The impact of these variables is the opposite in the case of failures than in the case of bankruptcies. This puzzling result may be due to the high degree of correlation between $IC_{i,C}$, and $IC_{i,S}$

(0,667) which obscure the estimation of their separate effects. In summary, the effect of the variables reflecting direct and indirect external constraints on failures is mixed and their economic impact is not remarkable.

[INSERT TABLE 5 HERE]

2.6.3. Additional Test on the Concentration Ratio

It can be argued that the concentration measure *HHI* based on COMPUSTAT data is open to criticisms because it only covers public firms, disregarding private firms (Ali et al., 2009). Therefore as a robustness test we also consider the four-firm concentration ratio (*CR4*), published on BEA as our alternative concentration measure.[19] The *CR4* is based on information on sales, receipts, or revenue of the largest four firms in an industry as a percentage of total industry sales, receipts, or revenue. For example, a *CR4* of 0,55 means that the largest four firms in the industry account for 55% of all industry receipts.[20]

As an additional test we classify industries as "competitive" or "concentrated" using dummy variables. Here we consider three commonly used criteria to classify competitive and concentrated industries. First, if the concentration ratio is above 0,4, the industry is considered to be concentrated, and thus we include the variable, *Dummy(0,4)* that equals to one if the concentration ratio is over 0,4, and is zero otherwise. Second, an industry is regarded as *competitive* if the concentration ratio ranges between 0 and 0,5, as *medium concentrated* if it varies from 0,5 to 0,8 percent, and as *highly concentrated* if it is over 0,8 percent. Therefore we construct the dummy variable, *Dummy (0,5)* equals to one when the concentration ratio is above 0,5 and otherwise is zero. Moreover we also consider the variable *Dummy(Medium)* that equals to one if the concentration ratio is larger than the average value of concentration ratios in a given year and otherwise is zero.

Furthermore, we split the sample into two periods. The first one is from 1998 to 2009 to be consistent with previous analysis, and the second one is from 1990 to 2009 due to available *CR4* data.

[19] The website is http://www.census.gov/econ/concentration.html. Notice that the Census HHI is available only for manufacturing industry, we choose the four-firm concentration ratio which is available for most industries).
[20] Due to some limitations on CR4 data from BEA, we have to do some adjustments in matching CR4 to CRSP/COMPUSTAT data.

The summary statistics of *HHI* and *CR4*,[21] indicate that the median (mean) of *HHI* is 0,2 (0,187) for the period of 1990–2009 and 0.294 (0,281) for 1998–2009 respectively. The median (mean) of *CR4* is 0,318 and 0,324 for the period of 1990–2009 and 0,334 and 0,351 for 1998–2009 respectively. Both mean and median on *CR4* are larger than those on *HHI.* The Census-concentration ratios naturally should be larger than COMPUSTAT-based concentration ratios, since the *CR4* includes both public and private firms, whereas the *HHI* only uses public firms' information, and in some sectors it is not unlikely that some private firms are those firms with relative larger revenue, sales, or receipts.

Table 6 reports the estimation results from logit regressions for failures and bankruptcies using the *CR4* or dummy variables and the six control variables (EXRET, RSIZ, SIGMA, NI/TA, TL/TA CASH/TA). To save space, the table only displays the estimation results on industry concentration related variables since the impact of the control variables is similar to Tables 4 and 5. The results on bankruptcies (failures) are shown in left hand side (right hand side) of Table 6, and on *HHI* (*CR4*) are reported in Panel A (Panel B) of Table 6 respectively.

[INSERT TABLE 6 HERE]

Overall the results support Hypothesis 1. First, the *HHI* (the first row of Panel A) still remains significantly positive when data period is extended to 1990–2009, and the *CR4* (the first row of Panel B) also shows positive significance, except for the case of failure during period 1998–2009. Second, we turn to explore whether the Hypothesis 1 still holds when an industry is classified into either competitiveness or concentration with the use of alternative dummy variables as substitution for *HHI* or *CR4*. In terms of *HHI*-based dummy variables (see Panel A), it shows consistent positive significance. For *CR4*-based dummy variables (see Panel B), estimation results are always positive and significant, in particular for bankruptcies. However in the case of failures, only the *Dummy(0,4)* variable is significant. The non-significant results on *CR4*-based variables might be attributed to some limitations of using data from the Census: (1) it is updated every five year, whereas COMPUSTAT-based variables are renewed annually; (2) it is not available for all industries, which implies that the sample does not cover the whole economy.

[21] The table of summary statistics on *HHI* and *CR4* is available upon request.

2.7. Robustness Tests

As a robustness test, we consider more COMPUSTAT-based concentration measures employed by other studies, including (1) the *Assets-based HHI*, and (2) *Sales-based HHI on **n**-digit Industry Code*. We also use *Eight-firm, Twenty-firm, and Fifty-firm Concentration Ratio* as alternative Census-based concentration measures to re-examine the industry effect on bankruptcies or failures. Our main results are not materially affected by changes in the concentration measures.[22]

2.8. Conclusion

We empirically investigate the connection between industry structural constraints and firms' failure prediction based on two dimensions: (1) the intensity of industry concentration, and (2) the degree of dependence on customers and suppliers. The key results are: (i) failure and bankruptcy probabilities increase when the degree of competition in a given industry decreases., (ii) the probability of bankruptcy is higher for firms in industries with relatively stronger customer dependency but this factor does not affect failure probabilities. One implication of this paper is that the government, investors, and entrepreneurs should realize that a firm bears more failure and bankruptcy risk when it operates in highly concentrated sectors

[22] All tables that contain robustness results are available upon request.

Appendix A

Description of the Independent Variables

We use a dynamic logit regression to analyze bankruptcy/failure prediction, This section describes the construction of the explanatory variables,

Excess return (EXRET) is computed from the sum of monthly returns minus the value-weighted CRSP NYSE/AMEX/NASDAQ index return over past twelve months, Low past excess returns should increase the chance of bankruptcy, because the decrease in equity value increases leverage and therefore default probabilities,

Relative size (RSIZ) is the logarithm of each firm's market equity value (outstanding shares × stock prices) divided by the total NYSE/AMEX/NASDAQ market equity value at the end of June, The lower the relative size, the higher the default probability, such that we expect a negative relationship between RSIZ and bankruptcy likelihood,

Volatility (SIGMA) denoted as annualized volatility is obtained based on the standard deviation of the residuals from regressing monthly stock returns on the monthly value-weighted NYSE/AMEX/NASDAQ index returns over the past twelve months, It measures the probability of the firm's asset values being below the default threshold, so we expect that higher SIGMA indicates a higher probability of bankruptcy or failure,

NI/TA, or the firm's net income divided by total assets, This ratio typically represents a firm's profitability, and we expect a negative effect on bankruptcy,

TL/TA, or the firm's total liabilities divided by total assets, As a proxy of leverage, a firm with high TL/TA tends to have high probability of bankruptcy,

CASH/TA, or the firm the ratio of a company's cash and short-term assets to its total assets, This ratio measures a firm's liquidity, and we expect a negative effect on bankruptcy, Firms often default because of their inability to pay their financial obligations on time due to the imbalance between their cash inflows and outflows (see Laitinen and Laitinen, 1998), Note that we remove any firm-year observations with less than ten monthly returns from the volatility estimation and any yearly observation with missing accounting variables.

Appendix B

Delisting codes in the CRSP Database

Delisting Code	Definition
400	Issue stopped trading as result of company liquidation
550	Delisted by current exchange - insufficient number of market makers
551	Delisted by current exchange - insufficient number of shareholders
552	Delisted by current exchange - price fell below acceptable level
560	Delisted by current exchange - insufficient capital, surplus, and/or equity
561	Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets
570	Delisted by current exchange - company request (no reason given)
572	Delisted by current exchange - company request, liquidation
573	Delisted by current exchange - company request, deregistration (gone private)
574	Delisted by current exchange - bankruptcy, declared insolvent
575	Delisted by current exchange - company request, offer rescinded, issue withdrawn by underwriter
580	Delisted by current exchange - delinquent in filing, non-payment of fees
581	Delisted by current exchange - failure to register under 12G of Securities Exchange Act
582	Delisted by current exchange - failure to meet exception or equity requirements
583	Delisted by current exchange - denied temporary exception requirement
584	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing

CHAPTER 3

Industry characteristics and financial risk spillovers

3.1. Introduction

In many countries, the financial sector is a key funding source for industrial and service (i.e., real economy) firms with limited internal funds. Intuitively then, real economy firms' risk and return should be strongly affected by the vagaries of the financial sector—in particular, its profitability and stability. The financial crisis of 2007–2009 illustrates a situation in which acute distress in the financial sector caused a severe credit crunch, with devastating effects on the real economy. Therefore, it is not surprising that the links between the financial sector and real economy sectors have been widely explored. Previous literature has focused on industrial real output (see Rajan and Zingales, 1998),[23] stock market returns (Baur, 2011),[24] and the links between other measures of returns and profitability. However, the linkage between risk in the financial sector and that in the real economy sector has received little attention so far. This is surprising, given the aforementioned evidence from the 2007–2009 financial crisis. This article is an attempt to fill this literature gap with two contributions: a new measure of tail risk spillovers and some empirical evidence on this important subject.

We explore the extent to which the financial industry's risk spills over to industrial and service sectors' risk from several perspectives. First, we determine whether risk spillover from the financial sector to real economy sectors existed over the past decade and to what extent the intense distress of the financial sector in the 2007–2009 financial crisis affected it. Second, we consider both volatility and tail risk spillover, because they provide different insights on risks. Note that whereas volatility characterizes dispersion from average returns, tail risk focuses on the left tail of the return's distribution. Third, we investigate whether tail risk spillover is affected by the real economy sector's product market structure (competition versus concentration). Fourth, we investigate whether the tail risk spillover is driven by three industry

[23] Rajan and Zingales (1998) point out that the industry's growth is related to its dependence on external sources of finance, stemming from industry-specific technological factors, which can affect initial project scale, gestation period, cash-harvest period, and further investment needs. Accordingly, an extensive body of literature tests the impact of banks on the real economy at country, industry, and firm levels across countries and over time (Beck et al., 2000; Beck and Levine, 2002, 2004; Cetorelli and Gambera, 2001; Chava and Purnanandam, 2011; Cole et al., 2008; Claessens and Laeven, 2005; Dell'Ariccia et al., 2008; Hoggarth et al., 2002; Kroszner et al., 2007; Levine, 2005; Vives, 2001).
[24] Baur (2011) finds that the 2007–2009 crisis led to an increased comovement of returns among financial sectors' stocks across countries and between the financial sector's and real economy sector's stock returns.

characteristics: net debt financing, valuation, and investment. These characteristics are closely related to the industry's investment opportunities and future perspectives.

Furthermore, we develop a new proxy for capturing financial tail risk spillover: conditional coexceedance (CCX). The CCX measures the frequency of simultaneous extreme negative stock returns in the financial and real economy sectors. We also compute probabilities of tail risk spillover at the industry level over time, distinguishing crisis and non-crisis periods. Finally, we study the determinants of the CCX measure in terms of the industry's structural characteristics. We use U.S. stock market data for 2001–2011. The main empirical results are as follows: (1) Increases in financial industry's volatility and tail risk cause corresponding increases in the real economy sector's risk variables, and the effect of this spillover is stronger during a financial crisis period. (2) The tail risk spillover from the financial sector to the real economy sector, as measured by the CCX, is stronger if the real economy industry is more competitive, uses a high proportion of net debts, and has a relatively low level of valuation and investments.

The study is related to several strands of literature. Our results are consistent with Diebold and Yilmaz (2012) in the sense that the financial sector's volatility generally increases sharply and spills over to other economic sectors in times of financial distress.[25] Furthermore, our study pertains to tail risk dependence (e.g., Bae et al., 2003), in that we introduce the CCX measure and document the financial sector's role in affecting the industrial sector's tail risk. We document a risk increase in real economy sectors stemming from increases in the instability of the financial sector and the consequent negative impact on the economy, in line with Kroszner et al. (2007). Moreover, while recent evidence supports the view that the intensity of competition in a given industry has significant implications for firms' cash flows and stock returns (Hoberg and Phillips, 2010; Hou and Robinson, 2006), the significant effect of the degree of competition on the linkage of tail risks between the real economy and financial sectors is a novel result. Finally, we provide a possible reason for the higher risks of highly competitive industries (Valta 2012): their tail risk connection with the financial sector.

In summary, our contributions to literature are as follows. First, we develop novel empirical methodologies for testing the effect of volatility and tail risk spillover from the financial to the real economy sectors before and during the 2007–2009 financial crisis. Second, our empirical analysis in the U.S. market

[25] The leading role of the financial sector with respect to aggregate volatility is also documented in Houston and Stiroh (2006), Wang (2010), and Cheong et al. (2011).

over the preceding decade confirms that risk spillovers (in both volatility and tail risk dependence) increased during the crisis period. Third, we relate the financial risk spillover measure CCX to the real economy industry's product market structure, investment opportunities, and valuation. Finally, we empirically document that the effect of the real economy industry characteristics on tail risk spillover measures exhibits variation across industries: It is stronger for industries that face more competitive product markets, use higher net debts, and have lower levels of valuation and investment.

The study in turn provides two key implications. First, our findings demonstrate the close connection between the financial and real economy sectors. This result is important for practitioners, because it supports the view that difficulties in the financial sector are, sooner or later, followed by large increases in uncertainty in other industries. Second, our CCX-based results imply that the financial sector's extreme returns are a concurrent indicator of real economy sectors' extreme returns. Therefore, our CCX measure can provide warning signals of impending turmoil in stock prices of real economy firms when a financial crisis materializes. Policy makers and regulators interested in evaluating the economic costs of financial crises should find our results useful. In particular, one of the Basel III capital accord's key objectives is to reduce the risk of spillover from the financial sector to the real economy. Given that the purpose of Basel III norms is to reduce the frequency and severity of these spillovers, our modeling approach could be used to assess their effectiveness. Finally, because real sectors, which require debts and whose value and investment activity are relatively lower, are prime candidates for depreciation in the wake of the financial sector crisis, investors can benefit from our findings as well.

The remainder of the paper proceeds as follows. The next section discusses how risk spillover and industry characteristics interact. Section 3 addresses empirical methodologies. Section 4 introduces the database and construction of the industry characteristic variables. Section 5 discusses the empirical results. Section 6 describes robustness tests, and Section 7 concludes with a discussion of limitations and suggestion for further research.

3.2. Risk spillover and industry characteristics

3.2.1. Volatility spillover

Evidence regarding the extent to which risk increases in the financial sector spill over to risk increases in industrial sectors is relatively scarce. Houston and Stiroh (2006) find that in the U.S. economy, the financial sector's volatility has had a significant and negative impact on economic growth from 1985 to 1994.[26] Noting volatilities, Wang (2010) shows that the financial sector's volatility leads non-financial sectors' in the U.S. market from 1963 to 2008, and Cheong et al.'s (2011) results support this view in the United Kingdom's economy from 1990 to 2010. However, to our knowledge, there is no evidence from other economic areas or time periods.

A related question is whether the 2007–2009 financial crisis affected the risk spillover mechanism from the financial sector to the real economy. If a sudden loss occurs within the financial system, its contractionary impact on real economy sectors is bound to be strong (see Kroszner et al., 2007). The 2007–2009 crisis has led to an increased comovement between the financial sector's and real economy's stock returns (Baur, 2011). Recent evidence indicates that the 2007–2009 financial crisis has had a negative impact on industrial sectors' investment activities (Campello et al., 2010).[27] Finally, the shortage of external funding weakens firms' operating flexibility during crisis periods because firms face budget constraints, reducing their investments and thereby increasing their equity risk (Ortiz-Molina and Phillips, forthcoming). In line with previous evidence, we hypothesize:

Hypothesis 1: Volatility spillovers occur from the financial sector to real economy sectors and are stronger during financial crises.

3.2.2. Tail risk spillover and product market structure

In contrast to volatility, which is characterized by dispersion from average returns, tail risk concentrates on the left tail of returns' distribution. The left tail risk has been addressed in extant literature. Bae et al. (2003) study extreme comovements between stock returns using exceedance correlations. Hartmann et al. (2004) employ a non-parametric measure, using extreme value theory to gauge spillover effects between stock and bond markets.

With regard to the linkage of tail risk between financial and industrial sectors, Christiansen and Ranaldo (2009) apply Bae et al.'s (2003) method to compare the financial integration of the old and new European

[26] It was a turbulent period for the U.S. banking sector. Large banks suffered huge losses from loans to developing countries. Savings and loans failures peaked in 1988 and 1989.

[27] They report that 86% of U.S. chief financial officers canceled or postponed attractive investment opportunities because they were unable to borrow externally.

Union countries' stock markets and find strong persistence of coexceedance for both regions, especially in lower tail coexceedance. Beine et al. (2010) measure stock market coexceedance using quantile regression and demonstrate that financial liberalization leads to an increase in the left tail's comovements. Fry et al. (2010) focus on the coskewness of market returns, showing spillover effects between the real estate and equity market within and between countries for the 1997 Hong Kong crisis and the 2007 subprime crisis. Thus, we expect tail risk spillovers to exist and be especially intense in downturns, a point that also became evident during the 2007–2009 financial crisis. Therefore, we hypothesize the following:

Hypothesis 2a: Tail risk spillovers occur from the financial sector to real economy sectors and are stronger during financial crises.

Next, we determine the effect of different product market structures on tail risk spillover. Valta (2012) studies U.S. firms from 1992 to 2007 and finds strong empirical evidence that banks charge significantly higher interest rates in loans given to firms in competitive environments because of their higher default risk and lower asset liquidation value. Moreover, Ortiz-Molina and Phillips (forthcoming) find that the cost of inflexible operations is higher for firms that face more competitive risk in product markets. Therefore, we predict that competitive industries experience more financial tail risk spillover than concentrated industries and hypothesize:

Hypothesis 2b: The stronger (weaker) the tail risk spillover from the financial sector, the higher (lower) the degree of competition in a given industry.

3.2.3. Tail risk spillover and industry characteristics

We further investigate the differential impact of various industry characteristics on the linkage between the financial sector's and real economy's risks. We consider three industry-level variables: industry net debt issuance, industry valuation, and industry investment.

A possible channel through which the financial sector affects industrial firms' growth and risks is the firm's external financing dependence. For example, beginning with Rajan and Zingales (1998), scholars have paid a great deal of attention to the degree of competition in the banking sector and how dependency on external financing across nonfinancial industries affects nonfinancial industries' growth and structure.[28] The evidence shows that sectors that are highly dependent on external finance tend to experience a substantially greater contraction of value added during banking crises (Kroszner et al., 2007). Real asset illiquidity increases for firms that have less access to external capital or are closer to default and face more competition (Ortiz-Molina and Phillips, forthcoming).

In particular, debt is the main source of external finance for firms' operating flexibility and real investment activities (Valta, 2012). Industries that depend heavily on debt financing sometimes encounter difficulties raising funds from the financial sector. In normal times, firms have a better chance of finding funding sources, from either the financial sector or selling assets. However, when the financial sector is in crisis, credit constraints may appear. In these circumstances, asset markets also likely are stressed. Thus, industrial sectors that have higher level of net debt may face a more negative impact when the financial sector is distressed, leading to an increase in tail codependence. In summary,

Hypothesis 3a: The higher the industry's debt financing, the greater the tail risk spillover from the financial sector.

Ortiz-Molina and Phillips (forthcoming) suggest that the problem arising from illiquid asset markets is more serious for firms with low valuations (low market-to-book ratios). Industrial sectors with higher valuations can obtain higher prices when selling assets and thus reduce their dependence on the financial sector. In addition, Fama and French (1995) and Chen and Zhang (1998) show that firms with low market-to-book ratios have persistently lower earnings, higher financial leverage, and more earnings uncertainty. That is, we expect that low market-to-book (low valuation) firms experience greater distress risks and therefore greater tail risks in connection with the financial sector during weak economic times. We hypothesize:

Hypothesis 3b: The higher the industry's valuation, the lower the tail risk spillover from the financial sector.

[28] Vives (2001) posits that the degree of competition in the financial sector is crucial when firms seek external financing. By adopting an industrial organization-based measure to assess the banking sector's competition, research shows that greater competition in the banking sector fosters the growth rate of financially dependent industries (Claessens and Laeven, 2005).

The level of investment in industrial sectors could also drive the financial tail risk connection. If firms cannot fully exploit their investment opportunities, they risk losing these opportunities, and thus market share, to rivals (Valta, 2012). In other words, the *ex ante* higher investment means firms fully exploit their investment opportunities and likely have more *ex post* internal financing resources, thus reducing their dependence on the distressed financial industry and their tail risks.

Hypothesis 3c: The higher the industry's investment, the lower the tail risk spillover from the financial sector.

In summary, we expect that some industry characteristics affect tail risk spillover more than others. We posit that this effect is stronger for more competitive industries, for industries that bear greater debts, and for those with low level of valuation and investment.

3.3. Empirical methodologies

3.3.1. Volatility spillovers

To model volatility spillovers, we follow Liu and Pan (1997) and employ a two-stage VAR-GARCH approach to demonstrate the mechanism of volatility transmission. However, we modify their approach in both the first and second stages to suit the problem at hand. Specifically, in the first stage, we model two equity index return series, corresponding to the U.S. financial sector and to a given U.S. industrial sector respectively, including both series in a VAR system. In doing so, we adjust for autocorrelations in each series as well as for cross-correlations between series. The residuals obtained after fitting the VAR model[29] are denoted $r_{i,t}$ and $r_{FIN,t}$, where *i* and *FIN* represent any non-financial industrial sector and the financial sector, respectively. Next, we standardize the series $r_{FIN,t}$ by means of a GARCH(1,1) process, as follows:

$$r_{FIN,t} \sim N\left(0, \sigma^2_{FIN,t}\right), \tag{1}$$

$$\sigma^2_{FIN,t} = \omega_{FIN} + \alpha_{FIN} r^2_{FIN,t-1} + \beta_{FIN} \sigma^2_{FIN,t-1} \tag{2}$$

$$\frac{r_{FIN,t}}{\sigma_{FIN,t}} = e_{FIN,t} \sim N\left(0,1\right), \tag{3}$$

[29] We chose the optimal lag in the VAR system using the Schwarz-Bayesian criterion.

where the standardized series is $e_{FIN,t}$. In the second stage, we model volatility spillovers using

$$r_{i,t} \sim N\left(0, \sigma_{i,t}^2\right) \tag{4}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i r_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 + \gamma_{i1} e_{FIN,t-1}^2 + \gamma_{i2} e_{FIN_{crisis},t-1}^2, \tag{5}$$

here $e_{FIN_{crisis},t-1}^2$ equals $e_{FIN,t-1}^2$ during crisis periods and zero otherwise.[30] There is a volatility spillover from the financial sector to the industry i if the coefficient γ_{i1} in Equation (5) is significantly positive. If the financial crisis amplifies the spillover, we expect the coefficient γ_{i2} in Equation (5) to be significantly positive as well.[31] As a robustness test, we also relax the normality assumption in Equations (1) and (4) by allowing residuals to follow student t-distribution.[32]

3.3.2. Tail risk spillover

3.3.2.1. Conditional coexceedance (CCX)

We define an extreme return, or exceedance, as one that lies below (above) the th (1 – th) quantile of the marginal return distribution. Formally, an exceedance for industry *i* at time *t* is defined as follows:

$$I_t^i\left(c\right) = \begin{cases} 1, & \text{if } r_t^i \in c \\ 0, \text{otherwise} & \end{cases}, \; t = 1, \ldots, T, \tag{6}$$

where $I_t^i\left(c\right)$ is the indicator function that equals 1 when the return r_t^i belongs to the set *c* and 0 otherwise. We arbitrarily define *c* as the set of asset returns located below the 5th quantile of the marginal distribution of daily returns.[33] Next, we posit a new measure of tail risk spillover from the financial sector to non-financial sectors in the spirit of Bae et al. (2003) by concentrating on the occurrence of simultaneous

[30] To obtain a crisis period encompassing all major financial and economic events, we adopt timelines provided by the Bank for International Settlements (BIS, 2009). The BIS study separates the timeline into four phases from the third quarter in 2007 until the end of 2009. Phase 1 spans from Q3 in 2007 until mid-September 2008 and is described as “initial financial turmoil.” Phase 2 (mid-September 2008 until late 2008) is defined as “sharp financial market deterioration,” and phase 3 is a phase of macroeconomic deterioration (until first quarter 2009). Thus, we define the crisis period as beginning in the third quarter of 2007 and ending in the first quarter of 2009.

[31] In Equation (5), the parameter γ_{i1} measures the spillover of shocks from a financial sector to another sector in normal periods; the parameter γ_{i2} measures the additional contribution of the crisis period to this spillover, and thus ($\gamma_{i1} + \gamma_{i2}$) reflects total effect of volatility spillover during crisis periods. If γ_{i2} is positive (negative), there is an additional increased (decreased) transmission of unexpected shocks from the U.S. financial sector to another sector i in the crisis period compared with non-crisis periods. Baur (2011) applies a similar setting to examine whether a contagion exists from the financial sector to the real economy by observing equity returns during 2007–2009.

[32] The results do not materially change in comparison with the normality assumption. Detailed results are available on request.

[33] We use the 5% quantile as the baseline. We also used the 1% and 2.5% quantiles as a robustness test, and the results are similar to those based on the 5% quantile. Detailed results are available on request.

negative extreme returns across assets as the key element of spillover.[34] We define our new measure, CCX, for a non-financial industry i at time t as follows:

$$CCX_t^i = I_t^i\left(c\right)\times I_t^{FIN}\left(c\right),\ t=1,...,T\ , \tag{7}$$

where CCX_t^i equals 1 if a non-financial industry i and the financial sector both have exceedances at time t and 0 otherwise. We name the measure "conditional coexceedance" to stress the key role of the financial sector in our measure and to distinguish it from the unconditional measures used in Bae et al. (2003).[35] The intuition supporting this measure is that a non-financial industry is exposed to tail risks, which are dependent on the simultaneous occurrence of extreme negative returns in the financial sector.

With this measure, we can compute the observed frequencies (likelihoods) of CCX for a given non-financial industry i. To do so, we compute the proportion of CCX over a fixed time horizon as follows:

$$\text{Prob}^i = n_1^i \Big/ \left(n_1^i + n_0^i\right), \tag{8}$$

where n_1^i is the number of ones and n_0^i is the number of zeroes in the indicator series in Equation (7). Furthermore, we separate Prob^i into two components to identify the relative frequency of CCX during crisis and non-crisis periods for an industrial sector i as follows:

$$\text{Prob}_{crisis}^i = \frac{n_{1,crisis}^i}{\left(n_{1,crisis}^i + n_{0,crisis}^i\right)}\text{, and }\text{Prob}_{non-crisis}^i = \frac{n_{1,non-crisis}^i}{\left(n_{1,non-crisis}^i + n_{0,non-crisis}^i\right)} \tag{9}$$

where $n_{1,crisis}^i$ ($n_{0,crisis}^i$) is the number of ones (zeroes) in the indicator series during the crisis period, and $n_{1,non-crisis}^i$ ($n_{0,non-crisis}^i$) is the number of ones (zeroes) in the indicator series during the non-crisis period.[36]

3.3.3. Determinants of CCX

Given that CCX take only non-negative integer values, we use the Poisson panel regression model to study their possible determinants. The dependent variable is the total number of daily CCXs observed in one

[34] Bae et al. (2003) claim that coexceedances are superior to the correlation coefficient if non-linearities in market behavior exist because coexceedances are not restricted to describe linear market behavior.

[35] Bae et al. (2003) define a coexceedance of n at t as the situation when n assets present exceedances on the same day t, whereas in our setting, one of units in a coexceedance must be the financial sector.

[36] When testing for equality of the likelihood during crisis and non-crisis periods, the standard normality-based tests are inappropriate because, by construction, both variables follow non-Gaussian distributions. Therefore, we employ the Wilcoxon rank-sum test, which is a nonparametric alternative to the standard two-sample t-test. The Wilcoxon test is based solely on the order in which the observations from the two samples. Because we want to know whether the distribution of $\text{Prob}_{\text{crisis}}$ is shifted to the right of distribution $\text{Prob}_{\text{non-crisis,}}$ in the "Empirical Results" section, we report tests for this one-sided alternative.

quarter in a given industry, and the explanatory variables are proxies for industry debt financing, industry valuation, industry investment, and control variables. We chose these explanatory variables because Hoberg and Phillips's (2010) evidence supports their prominent role in identifying the conditions that likely surround industry booms and busts.

Given that some of our explanatory variables are generated regressors, and therefore prone to the problem of errors in variables, standard ordinary least squares–based methods are suboptimal. Instead, we apply the estimation method based on the generalized method of moments (GMM) with suitable instrumental variables. This approach improves the efficiency and consistency of the estimates and mitigates to a considerable extent the errors-in-variables problem.[37] The baseline panel model specification is as follows:

$$CCX_{i,t} = EXP\left\{\alpha + \sum_{n=1}^{N} \beta_n X_{n,i,t-1} + \sum_{l=1}^{L} \delta_l control_{l,i,t-1} + Industry_{dummy} + Time_{dummy}\right\} + \varepsilon_{i,t} \quad (10a)$$

$$CCX_{i,t} = EXP\left\{\begin{array}{l} \alpha + \sum_{n=1}^{N} \gamma_n X_{n,i,t-1} \times D_{crisis,t} + \sum_{n=1}^{N} \omega_n X_{n,i,t-1} \times D_{non-crisis,t} \\ \quad + \sum_{l=1}^{L} \delta_l control_{l,i,t-1} + Industry_{dummy} + Time_{dummy} \end{array}\right\} + \varepsilon_{i,t}, \quad (10b)$$

where the dependent variable $CCX_{i,t}$ is the actual number of coexceedances observed quarterly for industry *i*. The dependent variable is regressed on the set of one-quarter lagged explanatory variables *X* and *control*. The vector of variables $X_{n,i,t}$ contains the industrial characteristic variables for industry *i* (net debt financing, spread from a normative value and a normative investment). The vectors $D_{crisis,t}$ and $D_{non\text{-}crisis,t}$ are dummy variables for the crisis and non-crisis periods, respectively. Both variables are designed to determine whether the relationship between CCX and industry effects is sensitive to the emergence of financial crisis. In particular, we define the crisis period as between the third quarter of 2007 and the first quarter of 2009. The vector of $control_{l,i,t}$ contains variables related to other industries' characteristics: volatility of profitability, debt cost, earnings per share, and size. We expected the impact of the volatility of profitability on CCX to be positive, because industries with higher profit instability would likely need more external financing and therefore are more exposed to financial sector upheavals. Similar reasoning applies to firms with relatively high costs of financing. In contrast, we expect firms and those with high earnings per share to be relatively less exposed to the financial sector's disturbances. Finally, the model includes industry and time dummies.

[37] We also employed the conditional maximum likelihood estimation (CMLE) method in line with Silva and Tenreyro (2006). Although most estimated coefficients are largely in agreement under both methods, a few are not, suggesting that the errors in variables problem may have material influence on the results. Therefore, we chose to present the GMM estimations in the main text. The CMLE results are available on request.

3.4. Database and industry characteristic variables

3.4.1. Database: Sample selection and industry classification

The empirical results are based on stock prices of firms traded in the U.S. market with available data from the Center for Research in Security Prices (CRSP) from January 2001 to December 2011.[38] We aggregate firm-level returns into value-weighted industry-level returns to test the industry-level volatility spillovers and tail risk spillovers. We work with 73 non-financial industries and one financial sector[39] (see Appendix A), adopting three-digit North American Industry Classification System (NAICS) codes. Regarding the construction of industry characteristic variables, we use quarterly accounting information obtained from COMPUSTAT databases.

We use the fitted Herfindahl-Hirschman index (HHI) that Hoberg and Phillips (2010) propose to identify competitive and concentrated industries.[40] Specifically, we define an industry as competitive (concentrated) if the fitted HHI is in the lowest (highest) quartile of the yearly sample distribution (see Valta, 2012).[41]

3.4.2. Industry characteristic variables

We construct three industry-level proxies for new opportunities and future prospects, including (1) net debt financing, (2) spread between the actual value and a normative value, and (3) spread between the actual investment and a normative investment. A detailed description of these variables follows.

3.4.2.1. Net debt financing

We measure a given firm's net debt financing in a given quarter as the firm's net debt issuing activity divided by total assets. The firm's net debt issuing activity is equal to long-term debt issuance minus long-term debt reduction (Hoberg and Phillips, 2010). Consequently, the industry's net debt financing is the total amount of net debt financing for all firms in the industry divided by total industry assets.

Those industries demanding higher levels of debt-like financing should be more vulnerable to the financial sector's distress. Thus, we expect the tail risk of industries with a greater dependency on debt

[38] We chose the initial year as 2001 because Bureau of Labor Statistics data (only available from 2001) are required to classify a sector's degree of competition.
[39] The three-digit NAICS codes for firms belonging to the financial sector are 521–525 and 531–533.
[40] Appendix B presents the details on the fitted HHI.
[41] We also use the highest and lowest 10% of fitted HHI as a robustness check, and the results do not change materially.

financing to be strongly linked with the financial sector's tail risk, which implies a positive coefficient in the regression.

3.4.2.2. Spread between the actual value and a normative value

We define an industry spread time-series valuation (hereafter, "spread valuation") using the procedure Hoberg and Phillips (2010) propose. First, we compute the normative value using the valuation model in Pastor and Veronesi (2003). We regress the log of the market-to-book ratio, $\log(M/B)$, of the reciprocal of 1 plus firm age (AGE), a dividend dummy (DD), firm leverage (LEV), the log of total assets (SIZE), current firm return on investment (ROE), and the volatility of profitability (VOLP) for each firm *i*.

$$\log\left(\frac{M}{B}\right)_{i,\tau} = a + bAGE_{i,\tau} + cDD_{i,\tau} + dLEV_{i,\tau} + e\log\left(SIZE_{i,\tau}\right) + fVOLP_{i,\tau} + gROE_{i,\tau}$$

$$,\tau = t-12,\ldots,t-1., \tag{11}$$

where book equity is constructed as stockholders' equity plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock. We compute the market equity by multiplying the common stock price by common shares outstanding. In addition, LEV is total long-term debt divided by total asset, and ROE is earnings divided by the preceding year's book equity. We calculate earnings as income before extraordinary items available to common stockholders, plus deferred taxes from the income statement, plus investment tax credit. We calculate the VOLP by regressing the ROE on lagged ROE for all firms in each industry and taking the variance of the residuals. We winsorize the VOLP and ROE variables at both the 1% and the 99% levels. We estimate the valuation regression mentioned previously using a rolling 12-quarter window of lagged data in each industry to obtain a set of coefficients that we apply to each quarter t, which provides a measure of predicted valuation. Finally, we compute spread (unpredicted) valuations, expressed as follows:

$$\text{Spread Valuation}_{i,t} = \log\left(\frac{M}{B}\right)_{i,t} - \text{Predicted}\left(\log\left(\frac{M}{B}\right)_{i,t}\right) \tag{12}$$

We winsorize this measure at the 1% and 99% levels. The spread valuation determines a firm's intrinsic worth based on its estimated future free cash flows. The industry-level spread valuation is the average over all firms in each industry. We posit that the higher the level of spread valuation, the lower its funding dependence on the financial sector, because highly valued industries usually can easily sell their assets if needed and therefore are less dependent on external financing. The implication is that we should expect a negative regression coefficient.

3.4.2.3. Spread between the actual investment and a normative investment

Similar to the case of spread valuation, we define an industry spread time-series investment (hereafter, "spread investment") as the variable of spread between the actual investment and a normative investment. First, we compute a normative investment based on Hoberg and Phillips's (2010) proposed methodology. That is, we regress the log of capital expenditures divided by lagged property, plant, and equipment; TOBINQ is Tobin's *q,* and the other independent variables are the same as in the regression in Equation (11):

$$\log\left(\frac{Invest_{i,t}}{PPE_{i,t-1}}\right) = a + bTOBINQ_{i,t} + cDD_{i,t} + dLEV_{i,t} + e\log\left(SIZE_{i,t}\right) + fVOLP_{i,t} + gROE_{i,t} \tag{13}$$

From the preceding model, we calculate spread investment as the difference between the actual investment and the predicted investment, as follows:

$$\text{Spread Investment}_{i,t} = \log\left(\frac{Invest_{i,t}}{PPE_{i,t-1}}\right) - \text{Predicted}\left(\log\left(\frac{Invest_{i,t}}{PPE_{i,t-1}}\right)\right) \tag{14}$$

We measure the industry-level spread investment by averaging over all firms in each industry. An *ex ante* higher spread investment means that firms fully exploit their investment opportunities and likely have more *ex post* internal financing resources, thus reducing their dependence on the financial industry. The previous reasoning implies a negative regression coefficient.

3.5. Empirical results

3.5.1. Summary statistics

Tables 7 and 8 present descriptive statistics of industry returns during the full sample period and during the financial crisis, respectively. The number of firms within each sector varies considerably. For example, Computer and Electronic Product manufacturing is the most populated sector, containing an average of 627 firms. In contrast, Wholesale Electronic Markets and Agents and Brokers contain an average of only 2.2 firms. Average returns are usually positive or zero in the full sample, and as expected, they are usually lower in the crisis period than in the full sample, with the exception of the Crop Production and Educational Services industries. Regarding the standard deviation, the crisis sample presents larger figures compared with the full sample, as expected. The least volatile sectors, in both the full sample (first figure) and the crisis period (second figure), are Food Manufacturing (0.010, 0.016), Beverage and Tobacco (0.011, 0.015), and Chemical Manufacturing (0.012, 0.017). In the full sample, the most volatile sectors are Hospitals (0.028) and Nursing & Residential Care (0.028). The two sectors that are the most volatile in the full sample are also the most volatile in the crisis period, with daily volatilities of 0.045 and 0.053, respectively. Notably, they present substantial one-day negative returns (Hospitals: –25.1% [2008/6/12] and Nursing –23.5% [2008/10/27]). The reasons for these significant drops in prices are as follows: The Hospitals sector contained only two stocks that day, and one of them (Chindex International, Inc), announced an unexpectedly bad result for its 2008 income, dragging the sector index with it. The Nursing sector also contained only two stocks and one of them (Sunrise Senior Living Inc.) suffered heavy losses that day due to negative news about its expected profitability. The Air Transportation sector also exhibited a significant negative return (–31.1%) in one day (2001/9/17); on that day, airline stock trading resumed after the September 11, 2001, attacks on the United States, and investors dumped these stocks given the uncertain prospects of the airline industry at that time.

It is worth mentioning that the financial sector has an average volatility of 0.019 in the full sample and 0.035 in the crisis sample, presenting lower volatility than the average of all sectors in the full sample (0.0198) and higher volatility than the average of all sectors in the crisis period (0.030). Jarque-Bera statistics are highly significant for both sample periods, suggesting that the normality assumption is unlikely to hold

[INSERT TABLE 7 HERE]

[INSERT TABLE 8 HERE]

Table 9 reports descriptive statistics of the dependent and explanatory variables in the Poisson regression analysis (see Equation (10)). The dependent variable, CCX, becomes larger in crisis period than in full sample. The variable net debt financing (ND_I) is always positive, on average, implying that real economy firms have positive net debt issuing activity in both the whole period and the crisis sub-period. Note, however, that debt financing needs increased in this last sub-period. The spread valuation (VAL_I) is small and positive in the full sample (0.1%) but strongly negative during the crisis, with an average undervaluation close to 17%. Regarding the spread investment (INV_I), the actual investment is always higher than the predicted investment and much higher (9.9%) during the crisis than in the full sample (4.6%) on average. This finding is surprising; investment should have constricted as the financial sector experienced distress, but its median value was slightly lower during the crisis and its standard deviation was much higher (1.59), compared with it (0.95) over the whole sample. The volatility of profits, leverage, and debt costs all increase in the crisis period, indicating the overall increase in firms' riskiness. Surprisingly, net income is always negative (–0.2%, –0.7%), implying negative earnings per share in the full period as well as during the crisis. Most variables present noticeable increases in their volatilities during the crisis, as expected.

[INSERT TABLE 9 HERE]

3.5.2. Volatility spillovers

Table 10 displays the results of the volatility spillover model shown in Equations (1)–(5). The table also shows the coefficient estimates in the full sample ($\gamma 1$) and the additional impact due to the crisis period ($\gamma 2$), with their corresponding t-statistics. The notation "c" indicates spillover. Several important findings are worth noting.

First, the coefficient estimate reflecting spillovers in the full sample ($\gamma 1$) shows that 55 of 73 industries suffer significant volatility spillovers from the financial sector (approximately 75% of all cases). The coefficient varies significantly across the sample of sectors. For example, the average size of the $\gamma 1$ coefficient is 0.34, but there are some industries with particularly strong spillover effects, such as Air Transport (2.35), Repair and Maintenance (0.89), and Amusement, Gambling, and Recreation Industries (0.81). In contrast, several industries seem unaffected by volatility spillovers, such as Textile Product Mills, Fabricated Metal Product Manufacturing, Furniture, and Nursing, among others.

Second, the coefficient estimate of $\gamma2$ measures the additional crisis-specific influence. A positive and statistically significant value of $\gamma2$ implies additional volatility spillovers in crisis periods. Table 4 shows that 61 of 73 industries (84% of all cases) exhibit an increase in volatility spillovers originating from the financial sector. Compared with normal periods (55 of 73), this spillover effect is stronger during crisis periods. For those 55 industries that suffer volatility spillover in non-crisis periods, 48 industries (87%) have additional volatility exposure to the financial sector during the crisis period. In contrast, of the 18 industries not exposed to volatility spillovers from the financial sector in non-crisis periods, 13 (72%) of them are exposed during crisis periods. This result implies that industries more sensitive to movements of financial sectors' volatilities in normal times are also more likely to have additional spillover effects during crises. The average size of the $\gamma2$ coefficient is 0.55, but the coefficient varies across sectors. This coefficient estimate is above 1.26 in three industries: Air Transport (2.38), Hospitals (1.26), and Ambulatory Health Care Services (1.26). In contrast, the coefficient estimate is below 0.06 in three industries: Data Processing, Hosting, and Related Services (0.06), Animal Production and Aquaculture (0.06), and Beverage and Tobacco Product Manufacturing (0.006). Overall, the evidence suggests that very few sectors are immune to the effects of the volatility spillovers in crisis times, and some sectors are more severely affected than others.

Furthermore, the degree of volatility spillover in the crisis period can be calculated by adding the coefficient estimates $\gamma1$ and $\gamma2$. The Air Transport industry has the highest value of ($\gamma1+\gamma2$) with 4.74, followed by Repair and Maintenance with 1.98. Compared with the average size of the $\gamma1+\gamma2$ coefficient of 0.9, the two industries' volatilities are strongly sensitive to the volatility of the financial sector.

Finally, there are only five industries whose volatilities seem to be unaffected in any circumstances by the financial sector's volatility: Animal Production and Aquaculture, Textile Product Mills, Electronics and Appliance Stores, Pipeline Transportation, and Personal and Laundry Services.

In summary, consistent with our Hypothesis 1, the empirical evidence generally supports the existence of volatility spillovers from the financial sector to real economy sectors and shows that these spillovers are usually stronger in the crisis period. The results suggest that volatility shocks originating from the financial sector are a source of risks that affect most other real economy sectors.

[INSERT TABLE 10 HERE]

3.5.3. *Tail risk spillover*

In this section, we present the results for the variable CCX, our proxy for financial tail risk spillover, with where the intuition that the larger the measure, the higher the spillover exposure. Table 11 shows the likelihoods of CCX over the whole sample and during crisis and non-crisis periods. In the full sample and on average, on less than 3% of the days, simultaneous negative extreme returns manifest in the financial and real sectors. However, the situation changes dramatically when we split the sample into crisis and non-crisis periods. In the first case, on more than 8% of the days, simultaneous extreme negative returns are manifest, whereas in the second case, this figure is less than 1.4%. Furthermore, and as the Wilcoxon test indicates, these averages are statistically different at any reasonable significance level. Indeed, all industries exhibit an increased tail risk comovement with the financial sector in the financial crisis period compared with the non-crisis period.[42] Industries whose tail risks are more exposed to financial sector distress in crisis situations are Fabricated Metal (12%), Printing (12%), and Forestry and Logging (11.34%); those less exposed are Animal Production (3.8%) and Wholesale Electronic Markets (4.1%). Overall, the empirical evidence supports Hypothesis 2a, in that tail risk spillovers from the financial sector to real economy sectors occur and are amplified during the financial crisis.

[INSERT TABLE 11 HERE]

3.5.4. *Competition versus concentration*

To test Hypothesis 2b, this section addresses whether the strength of tail risk spillover increases with the degree of the industry's competitiveness. We measure the CCX at yearly frequency because the competitive identification for each industry is updated every year. Specifically, for a given year, we use daily returns to compute the CCX, and we update the sample year by year. We classify the industries' degree of competition using the fitted HHI measure. We consider an industry concentrated if it belongs to the highest 25% of fitted HHI and competitive if it belongs to the lowest 25% of fitted HHI.

[INSERT TABLE 12 HERE]

[42] As a robustness test, we changed the starting point of the full sample from 2001 to 2003. The results do no change materially. We also changed the beginning of the crisis period to the first quarter of 2007. The results support our hypotheses even more strongly in that all industries exhibit an increased tail risk comovement with the financial sector in the financial crisis period compared with the non-crisis period. Details are available on request.

Table 12 presents the likelihoods of CCX for competitive and concentrated industries in Column 3 and 4, respectively, for each year as well as for the total sample. The CCX measure is always higher for competitive industries than for concentrated ones, though the differences are only significant (at 5%) for two years. However, the average difference using all years is positive and significant at the 1% level. Therefore, the data provide some support to Hypothesis 2b, in that competitive industries' tail risk may be more affected than concentrated industries' by extreme negative returns in the financial sector.

3.5.5. CCX and industry characteristics

3.5.5.1. The effect of industry characteristics

Next, we consider the impact of the variables of industry characteristics on outcomes of CCX, which represents the tail risk spillover from the financial sector to other industries. Table 13 displays the results of industry-level regressions of CCX on net debt financing, spread valuation, and spread investment, respectively (Equations (10a)). In Model 5, the most complete model, the impact of net debt financing is positively related to CCX, whereas spread valuation and spread investment are negatively related to CCX, as expected. The results are consistent with our Hypotheses 3a, 3b, and 3c. The spread valuation is the variable with the highest economic impact[43] on CCX, followed by size. The control variables have the expected signs and are all significant. The degree of fit is measured by the pseudo-R^2 increases when industry-level variables are included in the equation,[44] but the bulk of this increment is associated with the spread valuation variable, which confirms its relevant role.

[INSERT TABLE 13 HERE]

Next, we split each of the industry characteristics variables into non-crisis and crisis periods (Equation (10b)), the results of which are shown in Table 14. The effect of the variable net debt is weakly significant in the non-crisis periods but clearly significant in the crisis periods, as well as in the total sample. The spread valuation and spread investment are significant in both periods. Thus, we conclude that in the crisis period, the impact of the net debt variable on CCX increases, but the main results obtained in Table 13 remain unchanged, providing additional support to Hypotheses 3a, 3b, and 3c.

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[43] The economic impact of the variable X on the dependent variable Y is measured by the percentage change of Y when there is an increase of one standard deviation of X. Formally, we compute it as $[\exp(b_x s_x)*Y_m - Y_m]/Y_m$, where b_x is X's regression coefficient, s_x is X's volatility, and Y_m is the average sample value of Y.

[44] For panel regression models, standard measures of fit are not well defined. We take the square of the correlation between the original and fitted values of the dependent variable as the pseudo-R^2.

[INSERT TABLE 14 HERE]

3.5.5.2. The effect of competitive and concentrated industries

The degree of competition fundamentally affects firms' operating decisions and the riskiness of their business environment. As such, it is important to understand whether and how this characteristic of the product market structure affects financial tail risk spillovers. This section follows the main analysis by using Equations (10a) and (10b) on industry characteristic variables, but we focus on competitive and concentrated industries separately.

[INSERT TABLE 15 HERE]

Comparing competitive industries (see Table 15, Panel A) with concentrated industries (see Table 15, Panel B), the expected signs remain, but there are changes in statistical significance.[45] First, in the case of competitive industries, spread investment is not significant in the full sample, whereas it is significant in the non-crisis period. The data show some evidence of a positive (negative) impact of debt financing (spread investment) on CCX in the crisis (non-crisis) period. However, spread valuation and debt financing remain significant explanatory variables for CCX in all periods. Therefore, for competitive industries, the variables that seem to keep their explanatory power more consistently are net debt financing and spread valuation. The results are different for concentrated industries, where the only significant variable is spread valuation. A possible reason for this non-significant effect is that, in line with Ghosal and Loungani (1996), the impact of price uncertainty on the investment decision is small for relatively non-competitive industries, because the outcome depends on the strategic interaction within the industry. Therefore, the level of spread investment in concentrated industries might not necessarily provide useful information in predicting CCX.[46]

3.6. Robustness tests

We conducted a battery of robustness checks. First, we used distance-to-default (DD) as a proxy for tail risks. Second, we re-examined our main analysis by discarding some industries with abnormal returns. Third,

[45] To save space, we do not report estimation results for control variables in Table 15.
[46] Note that these results are based on a subsample of somewhat extreme observations (highly competitive or concentrated industries). It is worth emphasizing that we define competition (concentration) if the fitted HHI is in the lowest (highest) quartile of the yearly sample distribution.

we tested the reverse causality from economic sectors to financial industry. Fourth, we computed a dynamic CCX using a three-day window and determined its relationship with industry characteristics.

3.6.1. The exposure of distance-to-default

We adopted the aggregate Merton's (1974) DD metric to test tail risk spillovers and to determine the extent to which the spillover effect from the financial sector to other industries becomes worse during the crisis period.[47] To do so, we calculated monthly DD for each firm within a given sector, first using a rolling window and then averaging all firms to build an industry-level DD. To match the sample frequency of our control variables (quarterly), we aggregated the monthly DD to quarterly frequency. We ran two regressions to analyze the tail risk spillover from the financial sector to other industries and determine whether the spillover effect becomes more severe in the wake of financial crises.[48] The panel regressions are as follows:

$$DD_{i,t} = \alpha_i + \beta_{i1} \times DD_{fin,t-1} + \sum_{j=1}^{J} \beta_{ij} \times control_{j,t-1} + Industry_{dummy} + Time_{dummy} + \varepsilon_{i,t} \tag{15}$$

$$\begin{aligned} DD_{i,t} = \alpha_i + \beta_{i1} \times DD_{fin-non-crisis,t-1} + \beta_{i2} \times DD_{fin-crisis,t-1} \\ + \sum_{j=1}^{J} \beta_{ij} \times control_{j,t-1} + Industry_{dummy} + Time_{dummy} + \varepsilon_{i,t} \end{aligned}, \tag{16}$$

where $DD_{i,t}$ represents the distance-to-default for industry *i*, $DD_{fin,t-1}$ is the DD for the financial sector lagged one period, $control_{j,t-1}$ are a set of control variables lagged one period,[49] and $\varepsilon_{i,t}$ is the residual.

We included industry and time dummies to avoid estimation bias, and we estimated the coefficients by means of a Prais-Winsten regression robust to heteroskedasticity and contemporaneous correlation across panels. If there is significant impact of the lagged financial sector's DD on industry *i*'s DD, we expect that $\beta_{i1} > 0$ in Equation (15). In addition, if the financial crisis increases the impact of these spillovers, we should expect that $\beta_{i2} > \beta_{i1}$ in Equation (16).

Table 16 reports the empirical results. First, there is a significant and positive relationship between the industries' and the financial sector's DDs. The control variables are significant and have the expected sign.[50]

[47] The Basel Committee on Banking Supervision (1999) considers Merton's DD model an industry standard risk. We calculate DD in line with the bulk of the literature based on Merton's model (1974). Calculation details are available on request.

[48] The variable $DD_{fin-non-crisis}$ is equal to DD_{fin} multiplied by a dummy variable, which equals 1 before the thirdc quarter of 2007 and after the first quarter of 2009 and 0 otherwise. We obtained the $DD_{fin-crisis}$ variable by multiplying the DD_{fin} by a dummy variable equals 1 after the third quarter of 2007 and before the first quarter of 2009 and 0 otherwise.

[49] Industries' control variables are the volatility of profitability (VOLP), leverage, earnings per share (EP), and SIZE (defined as market value rather than total assets to avoid collinearity problems) for each industry.

Comparing the results of Model 1 with Model 2's enables us to investigate whether the influence of tail risk spillover is stronger during the crisis period. The evidence shows a larger estimated coefficient on crisis-specific DD, revealing that tail risk spillover is stronger during crisis periods. Overall, the results support Hypothesis 2a.

[INSERT TABLE 16 HERE]

3.6.2. The impact of extreme returns

Because we find extreme negative returns in some health care–related industries (e.g., Hospitals, Nursing), which could distort our analysis, we excluded those sectors and re-examined the relationship between CCX and industry characteristics. This reexamination involved only cases based on all industries and concentrated industries because these suspicious sectors are all identified as concentrated ones in our study. In general, our main analysis remains the same.[51]

3.6.3. Reverse causality: Volatility

To test for reverse causality in volatility spillovers from real economy sectors to the financial sector, we switched *i* and FIN in Equations (1)–(5) and re-estimated this set of equations for each industry *i*. The results provide little supportive evidence of significant volatility spillovers from non-financial sectors to the financial industry in the full sample period. However, in the crisis period, there are many cases of significant volatility spillovers from real economy sectors to the financial sector. As an additional test, we used the 30-industry daily data from the Fama-French website. The results are similar. Therefore, we conclude that in crisis periods, there is a complex feedback mechanism of volatility spillovers between the financial sector and many real economy sectors. However, we note that the initial shock to the economic system originated in the financial sector.

3.6.4. Reverse causality: Tail risk

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[50] The signs of these coefficients are consistent with simple economic intuition; for example, smaller firms tend to use more short-term debt than larger firms, which make the whole industry riskier and more prone to financial distress. An industry with higher volatility of profitability and higher leverage bears more risk and thereby decreases the DD (higher default probability). In line with the preceding statement, higher volatility of profitability and leverage will result in lower DD (higher default probability), whereas higher earnings per share and size will cause higher DD (lower default probability).

[51] To save space, the results in Section 3.6.2, 3.6.3, 3.6.4, and 3.6.5 are not included here but are available on request.

Possible feedback effects of tail events between the financial and non-financial sectors are difficult to take into account in our baseline setting, because by its very nature, the CCX_t^i measure focuses on concurrent events. To shed light on possible feedback effects, we used two additional CCX-based measures:

(i) $CCX_{(i,t,FIN,t-1)} = I_t^i(c) \times I_{t-1}^{FIN}(c), t = 1, \ldots, T$, which equals 1 if industry *i* has an exceedance on day *t* and the financial industry has an exceedance on day *t – 1*.

(ii) $CCX_{(i,t-1,FIN,t)} = I_{t-1}^i(c) \times I_t^{FIN}(c), t = 1, \ldots, T$, which equals 1 if industry *i* has an exceedance on day *t – 1* and the financial industry has an exceedance on day *t*.

We hypothesize that if there is a feedback effect and the financial and non-financial sector effects are causing each other, measures $CCX_{(i,t,FIN,t-1)}$ and $CCX_{(i,t-1,FIN,t)}$ should have similar likelihood. In contrast, if tail risk events tend to manifest first in the financial (non-financial) sector and subsequently in the non-financial (financial) sector, measure $CCX_{(i,t,fin,t-1)}$ should have higher (lower) likelihood than measure $CCX_{(i,t-1,fin,t)}$. To test this idea, we computed likelihoods for both measures across the full sample period, the crisis period, and the non-crisis period. Then, we computed average values of probabilities of CCX on all industries across different time periods. The results (available on request) suggest that the likelihood of measure $CCX_{(i,t,fin,t-1)}$ is significantly higher than the likelihood of $CCX_{(i,t-1,fin,t)}$ during the full sample and crisis periods. Therefore, the evidence suggests that in crisis and full sample periods, tail risk events occur first in the financial sector and then in non-financial sectors. However, in the non-crisis period, a feedback effect cannot be ruled out. Therefore, our assumption that in crisis periods, extreme volatility episodes begin in the financial sector and then spill over to other non-financial sectors seems to be borne out by the data.

3.6.5. Dynamic CCX

To assess the possible dynamic nature of CCX, we re-computed this variable using a moving three-day window. That is, we defined the CCX as including the financial sector's extreme returns within a moving three-day window. Then, we computed the likelihoods and re-estimated the base model regression of

Equation (10a) using this alternative measure as the dependent variable. We find that results are broadly consistent with our Hypotheses 2a, 3a, 3b, and 3c.

3.7. Conclusion

In this article, we propose a new approach to measure tail risk spillovers from one economic sector to other sectors: the CCX. We apply our approach to the financial sector and real economy industries in the United States from 2001 to 2011. We find large volatility and tail risk spillovers from the financial sector to many real economy sectors during this period. These spillovers are even stronger during the 2007–2009 financial crisis. In addition, we find evidence suggesting that the higher the degree of competition, the stronger these tail risk spillovers.

Three industry characteristics help explain the size of tail spillovers. The net debt financing has a positive effect on the size, whereas valuation and investment have a negative impact. The variable with the most relevant impact from the economic viewpoint is the valuation. Our results have implications for practitioners, in that they support the view that difficulties in the financial sector are sooner or later followed by large increases in uncertainty in many (but not all) industries and services. Furthermore, our results add to the increasing body of literature supporting the role of financial sector risk as a leading indicator of real economy overall risk and specifically tail risk. Our results may also help financial regulators evaluate the true overall economic cost of financial crises.

Looking forward, while recent research has shown that firm' capital structure decisions depend on industry structure (e.g., Bradley et al., 1984; MacKay and Phillips, 2005), the extent to which product market structure may affect tail risk remains an open question. We provide evidence linking product market characteristics to CCX, so our results point to a worthwhile avenue for further research. Another promising line of research is to explore the implications of our findings on loss aversion–based portfolio choice.

Appendix A

NAICS code	Industry name	NAICS code	Industry name
111	Crop Production	444	Building Material and Garden Equipment and Supplies Dealers
112	Animal Production and Aquaculture	445	Food and Beverage Stores
113	Forestry and Logging	446	Health and Personal Care Stores
211	Oil and Gas Extraction	447	Gasoline Stations
212	Mining (except Oil and Gas)	448	Clothing and Clothing Accessories Stores
213	Support Activities for Mining	451	Sporting Goods, Hobby, Musical Instrument, and Book Stores
221	Utilities	452	General Merchandise Stores
236	Construction of Buildings	453	Miscellaneous Store Retailers
237	Heavy and Civil Engineering Construction	454	Nonstore Retailers
238	Specialty Trade Contractors	481	Air Transportation
311	Food Manufacturing	482	Rail Transportation
312	Beverage and Tobacco Product Manufacturing	483	Water Transportation
313	Textile Mills	484	Truck Transportation
314	Textile Product Mills	486	Pipeline Transportation
315	Apparel Manufacturing	488	Support Activities for Transportation
316	Leather and Allied Product Manufacturing	492	Couriers and Messengers
321	Wood Product Manufacturing	493	Warehousing and Storage
322	Paper Manufacturing	511	Publishing Industries (except Internet)
323	Printing and Related Support Activities	512	Motion Picture and Sound Recording Industries
324	Petroleum and Coal Products Manufacturing	515	Broadcasting (except Internet)
325	Chemical Manufacturing	517	Telecommunications
326	Plastics and Rubber Products Manufacturing	518	Data Processing, Hosting, and Related Services
327	Nonmetallic Mineral Product Manufacturing	519	Other Information Services
331	Primary Metal Manufacturing	541	Professional, Scientific, and Technical Services
332	Fabricated Metal Product Manufacturing	561	Administrative and Support Services
333	Machinery Manufacturing	562	Waste Management and Remediation Services
334	Computer and Electronic Product Manufacturing	611	Educational Services
335	Electrical Equipment, Appliance, and Component Manufacturing	621	Ambulatory Health Care Services
336	Transportation Equipment Manufacturing	622	Hospitals
337	Furniture and Related Product Manufacturing	623	Nursing and Residential Care Facilities
339	Miscellaneous Manufacturing	711	Performing Arts, Spectator Sports, and Related Industries
423	Merchant Wholesalers, Durable Goods	713	Amusement, Gambling, and Recreation Industries
424	Merchant Wholesalers, Nondurable Goods	721	Accommodation
425	Wholesale Electronic Markets and Agents and Brokers	722	Food Services and Drinking Places
441	Motor Vehicle and Parts Dealers	811	Repair and Maintenance
442	Furniture and Home Furnishings Stores	812	Personal and Laundry Services
443	Electronics and Appliance Stores		

Appendix B

Classifying industries as competitive or concentrated

Following Hoberg and Phillips (2010), we classify industries as competitive or concentrated using an indicator that combines Compustat data with Herfindahl index data from the Census Bureau (U.S. Department of Commerce) and employee data from the Bureau of Labor Statistics (BLS).

We computed the fitted-HHI using a two-step procedure. First, for the manufacturing industries for which we had information on their HHIs including both public and private firms for every five years, we regressed the industry HHI (obtained from the Commerce Department) on three variables: the Compustat public-firm-only Herfindahl index, the average number of employees per firm using the BLS data (based on public and private firms), and the number of employees per firm for public firms using Compustat data. Second, we used the estimated coefficients from this regression to compute fitted HHI for all industries. This fitted HHI has the advantage of capturing the influence of both public and private firms. In the current study, we do not use these fitted HHI directly as an explanatory variable into any regression because of possible measurement errors. However, we consider the highest 25% (10%) of fitted HHI to correspond to concentrated industries and those with lowest 25% (10%) to correspond to competitive industries.

CHAPTER 4

Do Cash Holdings Influence Financial Risk Spillover? Firm Level Analysis in Europe

4.1. Introduction

Due to the financial and economic crisis that started in 2007 and Sovereign debt crisis of Europe zone, research on financial stability is facing new challenges and has embarked on a growing research agenda. There is a consensus to develop new and enhanced measures to understand the transmission channels from the financial sector to the real economy and to provide policy making with improved analytic tools. The growing literature on financial stability has been urged to expand the focus and to incorporate the interaction between the financial system and the rest of the economic agents and sectors. In Europe, in particular, financial markets and the banking sector have experienced tremendous instability, starting with the 2007-09 global financial crisis promptly followed by a sovereign debt crisis. This paper addresses the importance of risk transmitted from the financial sector to corporate sectors in the euro area.

We explore the extent to which financial industry's risk spills over to real economy firms via several perspectives. We ask three main questions. First, whether risks of financial sector spill over to non-financial firms in Europe? If yes, whether financial crisis event strengthens this tail risk spillover? Second, whether a firm's liquidity provision (e.g., cash holding) offsets its transmitted tail risks from the financial sector during crises? Third, whether a firm's financial condition (financially constrained or unconstrained) drives the effect of cash holdings on such transmitted risks?

To shed light on these questions, we hypothesize and examine three predictions. First, literatures support that there is a volatility spillover from financial sectors to real economy sectors both in US and UK (Wang (2010), Cheong et al. (2011)), and also exists extremely negative equity co-movements in US market, especially so during crises (see by Chiu, Peña, and Wang (2014)). Thus we presume there are tail risk spillovers from the financial sector to firms in real economy sectors. These spillovers are stronger during financial crisis. Second, some literature (see Ferreira and Vilela (2004) and Bates, Kahle, and Stulz (2009))[52]

[52] Bates, Kahle and Stulz (2009) document that the average cash-to-assets ratio for U.S. industrial firms more than doubles from 1980 to 2006 largely due to precautionary motives. Cash ratios increase because firms' cash flows become riskier; firms hold fewer inventories and receivables and are increasingly R&D intensive. Ferreira and Vilela (2004)

argue that cash holdings can be valuable when other sources of funds are insufficient to satisfy firms' demand for capital. Refinancing risk should be greater when credit market conditions are tighter. Harford, Klasa, and Maxwell (2013) find market puts a greater value on an incremental dollar of cash when the firm has significant refinancing risk. Therefore, we presume cash is valuable for firms in times of financial crisis through mitigating extreme risk propagated from financial sectors. Regarding the third question, existing literature document that financially constrained firms have greater cash reserves than unconstrained firms, and the role of cash holding is more valuable for financially constrained firms (see Faulkender and Wang (2006), Denis and Sibilkov (2010), Duchin, Ozbas, and Sensoy (2010), and Campello et al. (2012)). Moreover, Lin and Paravisini (2013) provide evidence on the causal link between financing constraints and the risk of corporate cash flows and returns. They document how firms' cash, payout, and investment policies respond endogenously to mitigate the impact of constraints on risk. Thus, we presume cash holdings mitigate risks propagated from financial sectors more for firms classified as financially constrained firms when credit market conditions tighten.

To examine these hypotheses, we construct a measure of capturing tail risk spillovers from financial sector to a non-financial firm, named CCX henceforth. The measure is firstly proposed by Chiu et al. (2014), and it regards a tail risk spillover as a simultaneous negative extreme movement between the financial sector and an industrial sector.[53] Then, we use Panel Poisson regression to test the role of cash holdings on such risk spillovers.

We study firms in 16 countries in Europe with period between 2003 and 2011. To have a clear analysis, we divide all countries into four regions: (1) Euro-periphery countries (Portugal, Italy, Greece, Spain, Ireland), (2) Euro-core countries (Austria, Belgium, Finland, France, Germany, Netherlands), (3) major European countries - but not euro countries (Sweden, Switzerland, Norway, Denmark), and (4) United

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investigate the determinants of corporate cash holdings in EMU countries and find that cash holdings are positively affected by the investment opportunity set and cash flows and negatively affected by asset's liquidity, leverage and size. Bank debt and cash holdings are negatively related, and capital markets development has a negative impact on cash levels.

[53] Different to that work, where they look at real economy impact at industry level, we instead analyze this impact at firm level. The firm-level evidence should be as much important as the aggregate-level one. The reason is that if different transmission channels imply different firm-level effects related to firm characteristics, one has a better chance to isolate and quantify the different channels. Such information is lost in the aggregate data. Also from corporate borrowers' perspective, the liquidity crisis in capital markets creates uncertainty about the ease of future access to capital, which impinged the fiscal health of many corporations.

Kingdom (UK). Overall, CCX is larger for Euro-periphery countries and less for UK, indicating that firms located in Euro-periphery suffer more risks stemming from the distressed financial sector.

Furthermore, our results are in supportive of the prediction 1 that CCX is more severe during financial crises periods across all regions. Moreover, our evidence favors the prediction 2 and 3 that cash provides important benefits to financially constrained firms in times of credit crunch and especially for financially constrained firms, restricted to two particular regions: Euro-core countries and UK We also document that CCX are positively associated with a firm's volatility, default risk, leverage, and size, whereas negatively related cash holding, return, and market-to-book ratio.

This study contributes to the growing literature in several dimensions. First, the relationship between the financial and real sides of the economy has long been a topic of intense interest and debate. Previous literature has investigated this linkage focusing on industrial real output (see Rajan and Zingales, 1998), stock market returns (Baur, 2011),[54] and the links between other measures of returns and profitability. However the linkage between the financial sector's risk and real economy risk has received little attention so far. The purpose of this paper is to fill the gap in the literature. Second, we complement the study of Chiu et al. 2014 by offering evidence that financial sectors spill over risks to real economy sectors at firm-level in Europe. Third, this paper establishes the new link between firms' liquidity management (e.g., cash holdings), firms' financing conditions (e.g., financial constraints) and tail risks propagated from distressed financial sectors. This complements the recent works that examine whether capital liquidity affects firm behavior focuses on the 2007-2008 credit crisis (e.g., Campello, Graham and Harvey (2010), Ivashina and Scharfstein (2010), Duchin, Ozbas, and Sensoy (2010)). We provide evidence showing that reserving cash is still valuable for financially constrained firms in that it enables firms to mitigate tail risks transmitted from the financial sector.

The study provides two key implications. First, our findings remark the close connection between the financial sector and non-financial firms. Investors are particularly keen to understand risks spilled over to real economy, in order to able to assess the benefits of portfolio diversification. Second, our results may also be useful to policy makers and regulators because they are interested in evaluating the possible economic

[54] Baur (2011) finds that the most recent crisis led to an increased co-movement of returns among financial sector stocks across countries and between financial sector's stock returns and real economy sector's stock returns.

costs due to financial crises. In particular, one of the key objectives of the Basel III capital accord is to reduce the risk of spillover from the financial sector to the real economy.

In the next section we describe literature reviews and prediction. The econometric methodology to be used in estimating is given in Section 3. Section 4 introduces the database and the construction of the firms' characteristic variables. In Section 5 discusses the empirical results. Robustness test are provided in Section 6. Section 7 concludes.

4.2. Literature Reviews and Prediction

4.2.1. Tail Risk Spillovers

The global financial crisis has led to an increased co-movement between financial sector's stock returns and real economy's stock returns (Baur, 2011), and has had a negative impact on industrial sectors' investment activities (Campello et al., 2010; Ortiz-Molina and Phillips, forthcoming). The evidence on the extent to which risk increases in the financial sector spill over risk to firms in real economy sectors is relatively scarce. Some studies explore such risk transmission channel by looking at *volatility*. For example, Wang (2010) shows that the financial sector's volatility leads non-financial sectors' in the U.S. market in the period from 1963 to 2008 and Cheong et al. (2011) support this view in the UK economy from 1990 to 2010. On the other hand, some studies document the linkage of *tail risks* between financial and industrial sectors. For example, Fry et al. (2010) focus on the coskewness of market returns, showing spillover effects between the real estate and equity market within and between countries for the Hong Kong crisis in 1997 and in the subprime crisis in 2007. Furthermore, literatures document that macro-economic shocks have significant impacts on corporate sector probabilities of default in the euro area (see Castren et al. (2010) and Carling et al. (2007)). Given that financial crises are often followed by macro-economic shocks, it implies that financial sectors' distress affects non-financial firms' default probabilities and thus their tail risks. Finally, Chiu et al. (2014) has offered direct evidence showing that financial sectors spill over risks to real economy sectors at industry-level, and such risk spillovers are stronger during weak economic times. So, our prediction 1 is as follows:

Prediction 1: There are tail risk spillovers from the financial sector to non-financial firms in Europe. These spillovers are stronger during financial crisis.

4.2.2. Cash Holdings and Tail Risks

Prior works have supported that cash holdings play an important role on firms' performance, but there is no clear cut on whether holding cash is good or bad. Some studies focus on the "dark side"- the potential for managerial abuse due to agency problems (e.g., Dittmar and Mahrt-Smith, 2007; Harford, 1999; Harford, Mansi and Maxwell, 2008; Pinkowitz, Stulz, and Williamson, 2006). In contrast, some works show a "bright side" or precautionary saving motive – seemingly excess cash may in fact benefit firms in times of dislocation in markets for external finance. The economic intuition is that cash holdings can be valuable when other sources of funds, including cash flows, are insufficient to satisfy firms' demand for capital. Firms facing external financing constraints can use available cash holdings to fund the necessary expenditures.

In terms of bright side, literatures also document cash can serve a valuable role in mitigating refinancing risk. For example, Harford, Klasa, and Maxwell (2012) support that cash reserves can reduce refinancing risks especially for firms whose debt has shorter maturity. The economic intuition is that cash reserves could enable the firm to keep fully investing in its growth opportunities and allow the firm to avoid selling off key firm assets to pay off debt that is coming due. Based the above statement, we set up our prediction 2.

Prediction 2: Cash is valuable for firms in times of financial crisis through mitigating extreme risks propagated from financial sectors.

4.2.3. The Role of Cash Holdings on Financial Constrained Firms

Presuming that cash holding is able to help to mitigate transmitted risks from the financial sector in times of crisis, is this effect systematically to all firms? We focus on investigating whether firms' financing conditions (financially constraint or unconstraint) drive this effect. The existing literatures document that financially constrained firms have greater cash reserves than unconstrained firms, and the role of cash holding is more important for financially constrained firms. For example Faulkender and Wang (2006), and

Denis and Sibilkov (2010) show that cash holdings benefit financially constrained firms by enabling these firms to fully invest in their growth prospects. Duchin, Ozbas, and Sensoy (2010) provide evidence that cash reserves are more important for financially constrained firms in mitigating post-crisis investment declines.[55] The authors argue that firms in response to constrained external financing accumulate cash to mitigate the potential value loss by forgone future investment opportunities. Most importantly, Lin and Paravisini (2013) provide evidence on the causal link between financing constraints and the risk of corporate cash flows and returns. They document how firms' cash, payout, and investment policies respond endogenously to mitigate the impact of constraints on risk. Froot, Scharfstein, and Stein (1993) point out financing constraints generate the rationale for active risk management. Collectively, these studies support the view that higher cash holdings are more valuable for financially constrained firms during crisis period. Therefore, our prediction 3 is as follows:

Prediction 3: Cash holdings mitigate risks propagated from financial sectors more for firms classified as financially constrained firms when credit market conditions tighten.

4.3. Empirical Methodologies

4.3.1. Tail Risk Spillover Measure

4.3.1.1. Conditional coexceedance CCX

We employ the measure proposed by Chiu et al. (2014) to capture tail risk spillover from the financial sector to non-financial firms.[56] We define an extreme return, or exceedance, as one that lies either below (above) the 5th (1-5th) quantile of the marginal return distribution. Formally an exceedance for industry i at time t is defined as

We define an exceedance for firm i at time t as

$$I_t^i(c) = \begin{cases} 1, & \text{if } r_t^i \in c \\ 0, & \text{otherwise} \end{cases}, \ t = 1, \ldots, T \tag{1}$$

[55] Campello et al. (2012) extend this result to European firms.
[56] Differently, we apply the measure on firm level, whereas they are on industry level.

where $I_t(c)$ is the indicator function that equals one when the return r_t^i belongs to the set *c* and equals zero otherwise.[57] Next, we measure tail risk spillover, named "*conditional coexceedance*" (henceforth CCX) for a non-financial firm *i* at time *t* as

$$CCX_t^i = I_t^i(c) \times I_t^{FIN}(c),\ t = 1, \ldots, T \tag{2}$$

where CCX equals one if a non-financial firm *i* and the financial sector both have exceedances at *t*, CCX is equal to zero otherwise. The intuition supporting this measure is that non-financial firms are exposed to tail risks which are dependent on the simultaneous occurrence of extreme negative returns in the financial sector.

4.3.2. Panel Poisson regression model

To examine whether cash holdings influence tail risk spillovers, we use a Panel Poisson regression specification, given the nature of CCX measure with only the non-negative integers. The dependent variable is the sum of daily conditional coexceedances observed in a quarter in a given firm, and the explanatory variables are cash holdings and other firm risk characteristic variables. They are (1) annualized volatility (*vol*), (2) distance-to-default (*dd*), (3) logarithm of market-to-book ratio (*logmb*), (4) quarterly return (*ret*), (5) logarithm of book asset value (*size)*, (6) ratio of book value of total liability to market value of asset (*tlmta*). The economic rationales of using these variables are described in Section 4.4.2. Besides, we use GDP per capita to control economic development,[58] and include year dummies to account for unobserved heterogeneity across years that may be correlated with the explanatory variables. Formally, the baseline panel model specification is as follows:

$$\log(CCX_{it}) = \gamma_i + \beta_1 cashmta_{it-1} + \beta_2 vol_{it-1} + \beta_3 dd_{it-1} + \beta_4 logmb_{it-1} + \beta_5 ret_{it-1} + \beta_6 size_{it-1} + \beta_7 tlmta_{it-1} + GDP_{it-1} + Time_{dummy} + \varepsilon_{it} \tag{3}$$

where the dependent variable $CCX_{i,t}$ is the actual number of coexceedances observed quarterly for firm *i* at time *t*. Furthermore, we perform Panel Poisson regression with fixed effects for two reasons. First a Hausman test rejects the random effects estimator in favor of a fixed effects estimator. On this basis, fixed

[57] We arbitrarily define *c* as the set of asset returns located below the 5th quantile of the marginal distribution of daily returns.

[58] To ensure that we can control for the effects of the business cycle and year specific events we use the GDP growth rate to control for cyclical effects (see Bougheas, S., Mizen, P., Yalcin, C., 2006)

effects specifications are preferred. Second, the inclusion of firm fixed effects can mitigate some endogeneity concerns, because such specification controls for unobserved sources of firm heterogeneity. Nevertheless, we also implement the random effects specifications as robustness.[59,60] We follow Peterson (2009) and correct for possible serial correlation and heteroscedasticity by clustering at the firm level.

To examine what extent that cash holdings influence CCX during the crisis period, we include crisis dummy and the interaction term of $cashmta \times crisis\_dummy$ into the regression, as displayed as follows.

$$\log(CCX_{it}) = \gamma_i + \beta_1 cashmta_{it-1} + \beta_2 crisis\_dummy_{it} + \beta_3 cashmta_{it-1} \times crisis\_dummy_{it} + \beta_4 vol_{it-1} + \beta_5 dd_{it-1} + \beta_6 logmb_{it-1} + \beta_7 ret_{it-1} + \beta_8 size_{it-1} + \beta_9 tlmta_{it-1} + GDP_{it-1} + Time_{dummy} + \varepsilon_{it} \quad (4)$$

In this model specification, we focus on the coefficient of β_3. A significantly negative sign of this coefficient indicates that cash holdings are able to further reduce financial risk spillovers during crises periods.

4.4. Database, Firms' characteristic Variables, and Criteria of Financial Constraint

4.4.1. Database: Sample Selection

Our sample contains data on financial sectors and non-financial firms from 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Norway, Spain, Sweden, Switzerland and United Kingdom. Different with identification strategy of Bartram, Taylor, and Wang (2007),[61] we divide the Euro-zone into Euro-periphery countries and Euro-core countries and regard UK as an independent group. Hence, we divide countries into four regions (groups): (1) Euro-periphery countries (Portugal, Italy, Greece, Spain, Ireland), (2) Euro-core countries (Austria, Belgium, Finland, France, Germany, Netherlands), (3) Other European countries - but not euro countries (Sweden,

[59] In random effect model we also include several controls for country, industry, and year effects. The results are similar as fixed effect and upon requested.
[60] The random effects model assumed the individual effects are independent, identically distributed and uncorrelated with the observed effect. This method will produce inconsistent estimator if the unobserved individual heterogeneity specific effect is correlated with explanatory variables. In which the fixed effects estimators will be more appropriate.
[61] Bartram, Taylor, and Wang (2007) conducted their data for twelve Euro-zone countries (France, Germany, Italy, the Netherlands, Spain, Finland, Belgium, Greece, Ireland, Portugal, Austria and Luxembourg) and five non-Euro European countries (UK, Switzerland, Sweden, Denmark and Norway).

Switzerland, Norway, Denmark), and (4) United Kingdom (UK).[62] The sample spans from 2003 to 2011, where we identify three mutually exclusive periods: (1) July 2007−March 2009 (named, Crisis_07_09); (2) May 2010−December 2011 (named, Crisis_EU); (3) period that does not cover Crisis_07_09 and Crisis_EU (named, Stable).[63]

Regarding the construction of firms characteristic variables, we use quarterly accounting information obtained from Compustat Global databases from 2003 to 2011, which provides financial and income statements for publicly traded companies accounting for over 96% of European market capitalization. Because the original data are denominated in local currencies, we convert variables to US dollar values by using exchange rates from the Board of Governors of the Federal Reserve System. To compute our tail risk spillover measure, security price of firms in each country are obtained from Security Price Global Compustat. We focus on industrial firms, but discard firms operated in utility sector (GIC= 5510). Finally, we have 103,189 firm-quarter observations. In addition, we eliminate observations with negative values for assets and winsorize our independent variables at both the 5% and the 95% level. Details on construction of financial variables are summarized in Table A.1.

Furthermore, this paper examines the tail risk transmission from the financial sector at industry-level to non-financial firms at firm-level, so we aggregate firm-level returns within the financial sector into value-weighted industry-level returns.[64]

4.4.2. Firms' Characteristic Variables

We attribute our variables of firms' characteristics to many categories, firms' risk characteristics (equity return volatility, distance-to-default), profitability (quarterly return), growth opportunity (market-to-book ratio), cash holding, sizes and leverage. The economic rationales of choosing these are described in the following.

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[62] We delete Luxembourg because the number of firms is less than 30, and include Ireland to the group "Euro-periphery". In addition, we regard UK as an independent group because the observation of firms is 28.13% of all sample.

[63] To obtain a crisis period encompassing all major financial and economic events, we adopt timelines provided by the Bank for International Settlements (BIS, 2009). Hence, in this paper, we define the Global financial crisis period starting in the third quarter of 2007 and ending in the first quarter of 2009. The recent European Monetary Union sovereign debt crisis is from May 2010 to December 2011.

[64] According to GIC group, the financial industry is composed of (1) 4010 Banks, (2) 4020 Diversified Financials, (3) 4030 Insurance, and (4) 4040 Real Estate.

Volatility (vol), shock propagation is more likely in a highly volatile environment overriding all asset classes. Unhedged or leveraged international allocations may also increase contagion. CCX are more likely to occur when volatility is pervasively high in all financial markets. *Distance-to-Default (dd)*, a market based indicator of the soundness of the firms. The *dd* indicates how far a firm's asset value is away from its default point, and thus we should expect the higher the *dd* and the lower the CCX. *Quarterly Return (ret)* is proxied for a firm's profitability, and thus we expect that the higher the quarterly return the lower the CCX. *Logarithm of market-to-book ratio (logmb)* is proxied for growth opportunity. Ortiz-Molina and Phillips (forthcoming) suggest that the problem arising from illiquid asset markets is higher for firms with low valuations (low market-to-book ratios). In addition, Fama and French (1995) and Chen and Zhang (1998) show that firms with high book-to-market ratios have persistently low earning, higher financial leverage, and more earnings uncertainty. That is, we can expect that higher book-to-market (low valuation) firms experience greater distressed risks, and then greater tail risks connection with the financial sector during weak economic times. *Cash Holding (cashmta)* is expected to reduce CCX because firms' reserving cash allow to better cope with adverse shocks when access to capital markets is costly. *Firm size (logsize)*, is usually considered as an important firm risk characteristic, but there is no clear expectation on the relationship between firm size and CCX. On the one hand, large firms are more diversified and thus should be relatively less exposed to financial sector's disturbances. On the other hand, large firms are likely to rely on external financing sources, and have high connection with financial sector, leading to suffer tail risk spillover from distress financial industry. The ratio of total liability to asset (*tlmta*) stands for a firm's leverage. A firm with higher leverage implies that it raises more funds externally from banks and public debt markets, and thus its risk is more sensitive to the risk of the financial sector.

4.4.3. Criteria of financial constraint

This paper also analyzes whether the influence of cash holding on CCX is driven by firm financial conditions, where we particularly look at a firm's constraint of financing. We follow literatures and consider three schemes of identifying a financial constrained firm. The detailed description of the chosen criteria is provided as below.

Firm size. In every quarter during 2003-2011, we rank firms based on their book value of total assets. We then assign those firms in the below (above) median of the firm size distribution to the financially constrained (unconstrained) group. This approach is used in literature (e.g., Erickson and Whited (2000); Almeida, Campello, and Weisbach (2004); and Acharya, Almeida, and Campello (2007)), and the intuition is that smaller firms are less well known, and they will be more vulnerable to capital market imperfections.

Age. We rank firms based on their age over the 2003 to 2011 period, and assign to the financially constrained (unconstrained) group those firms in the bottom (top) median of the age distribution. The rankings are again performed on an quarter basis. The younger firms are attributed to more financially constrained group in line with Hadlock and Pierce (2010), proposing that firm size and age are particularly useful predictors of financial constraint levels.

Annual payout ratio. In very year over the 2003 to 2011 period, we assign annual cash payout ratio distribution below (above) the median are classified as constrained (unconstrained) firms to the financially constrained (unconstrained) group. This approach is widely applied in literature, such as Almeida, Campello, and Weisbach (2004). The intuition follows from Fazzari, Hubbard, and Petersen (1988) argue that unconstrained firms are more likely to have higher payout ratios, while constrained firms are likely to have lower payout ratios.

We report the correlation matrix among three criteria of financial constraint in A.2. Generally speaking, correlations are not high, ranging from 0.15 to 0.33, indicating that the three identification criteria are not perfectly substitutable, and our financial constraint criteria complement each other.

4.5. Empirical Result

4.5.1. Summary Statistics

Tables 1 provides information on the number of observations, firms across European countries, firms across different regions, and descriptive statistics for firms' key financial variables in each country.

In Panel A of Table 17 the number of observations and the distribution of CCX vary widely across countries. The maximum number of firms is UK (1356), and four countries which Austria, Belgium, Ireland,

and Portugal has less than 100 firms. The total number of firms in the full sample is 4320. We note that CCXs are indeed prevalent in European countries, with the larger number of country Italy, Greece, and Spain respectively (0.949, 0.925, and 0.922). The least *dd* (3.069), *logmb* (-0.179), and *ret* (-0.024) were all occurred in Greece, which is somewhat explains why firms operated in that country have high level of CCX. Other two negative returns appeared in Italy and Portugal (-0.012, -0.003). Besides, firms in Portugal and Italy have relative higher leverage compared with other countries (0.659, 0.624). The Panel B reports summary statistics across different regions in terms of CCXs and firms' characteristics. We find euro-periphery performs highest of CCX and *tlmta*, while lowest of *dd*, *logmb*, and *cashmta*. Since 2010, countries in euro-periphery, including Greece, Ireland, Portugal, Spain and Italy, have faced some episodes of heightened turbulence in their sovereign debt markets. On the other hand, UK suffers less tail risk spillover from financial industry.

[INSERT TABLE 17 HERE]

4.5.2. Preliminary Results

Panel A, B, and C of Figure 3 plot CCX over the period of 2003-2011. It is clear to observe that most countries displayed highest levels of CCX during 2007-2009 global financial crisis, and second highest occurred in times of European debt crisis (May 2010 to December 2011), except Portugal. The crisis that originated in the subprime mortgage market in the US was strongly felt in all international financial sectors across the globe. While it started in the credit market in summer 2007, its destructive force was not fully sensed until the beginning of the first quarter of 2008.

The assessment of the effect of tail risk spillover from financial sector on different areas and time periods is provided by Table 18. The Panel A of Table 18 shows summary statistics of CCX across different areas and time periods. We observe the most frequency of CCX occurred in Euro-periphery at full, stable, and EU debt crisis period, whereas the UK is relative stable because of least CCX frequency. The sovereign risk is indeed substantially spread out in many Europeans economies, and in particular among the euro area periphery (Greece, Ireland, Portugal, Spain and Italy). During the global financial crisis, the non-Euro area performs the highest CCX frequency. This circumstance could explain no countries could be escaped from world-wide credit crunch.

In advanced, we test the differences on CCXs between two different areas for a given time period (see Panel B of Table 18). When testing for equality of the frequencies during different period, the standard Normality-based tests are inappropriate because, by construction, both variables follow non-Gaussian distributions. Therefore we employ the Wilcoxon rank-sum test which is a nonparametric alternative to the standard two sample t-test. There are two things needed to be noted. First of all, we find that there exists maximum difference and are significant occurred in euro-periphery and UK in terms of full, stable, and EU debt crisis period (0.334, 0.137, and 0.804). Second there is no significant difference of tail risk spillover between Non-Euro area (exclude UK) and UK during the global financial crisis. It demonstrated these two areas are all suffered extremely negative variation. Overall, the empirical evidence supports prediction 1 in the sense that we do find tail risk spillovers from the financial sector to real economy sectors, these spillovers being amplified during the period of financial crisis.

[INSERT FIGURE 3 HERE]

[INSERT TABLE 18 HERE]

4.5.3 . Baseline Regression Results

Table 19 gives the results for our baseline regressions. Model (1) to (5) report the results of Panel Poisson regression as proposed in equation (3) for the full sample and subsamples on different regions. In the case of full sample (Model 1), as expected, the variables of *vol* and *tlmta* are positively related to CCX, whereas the variables of *dd*, *ret*, *logmb*, *cashmta* are negatively associated with CCX. We observe the coefficient of size shows a positive sign, indicating that larger firms are likely having higher level of CCX. Moreover, the *vol* is the most influential determinant to CCX because it shows the greatest degree of economic impact[65] (33.22%) compared with other variables. The signs of these coefficients are consistent

[65] Economic impact=[exp(std*coef)*mean(CCX)-mean(CCX)]/mean(CCX). This measures percentage change of CCX when the ratio of cash-to-asset moves one standard deviation.

across four subsamples, although their significant levels are various. By looking at economic impacts, the most significant variable determining CCX in Euro-core (Model 3) and Non-Euro (Model 4) is the same as in the case of full sample, the *vol*, whereas it becomes *tlmta* for euro-periphery region (Model 2) and *size* for the UK (Model 5).

[INSERT TABLE 19 HERE]

Next, we investigate whether the cash holding serves as a particular role during financial crises, in that it can mitigate CCX. We implement the regression as described in equation (4), and estimation results are reported in Table 20. Using the full sample (Model 1), we observe that the coefficient along with the variable $cashmta \times crisis\_dummy$ is negatively significant. This result is consistent with our prediction 2 that reserving cashes can provide a buffer against shocks stemming from the distressed financial sector. During 2007-09 crisis, the estimated coefficient along with cash is from -0.428 to -0.724 (-0.428+ -0.296) in 16 European countries. The economic impact on this analysis is from -3.3% to -5.5%. It can be interpreted as one standard deviation increase in the ratio of cash holding significantly decreases 3.3% of CCX in tranquil times to 5.5% of CCX during 2007-2009 global financial crisis period.

However, this effect does not systematically appear in Europe, where it only exists only for Euro-core countries and UK. For Euro-core countries, the estimated coefficient along with cash is from -0.278 to -0.896 (-0.278+ -0.618), and the economic impact is from -2.2% to -6.8%. For UK, the estimated coefficient along with cash is from -0.446 to -1.072 (-0.446+ -0.626), and the economic impact is from -3.5% to -8.1%.

Summing up the overall evidence is consistent with our prediction 2 in the sense that larger corporate cash reserves help to mitigate tail risks from distressed financial sector, and the advantage of carrying cash are restricted to the Euro-core and UK.

[INSERT TABLE 20 HERE]

4.5.4 . Financial constrained firms vs. unconstrained firms

As shown in the above, cash holdings seem to be able to mitigate transmitted risks from the financial sector in times of crisis. We further examine whether firms' financing conditions (financially constraint or unconstraint) drive this effect. Firms are considered as unconstrained when they face favorable external financing conditions, i.e. they can increase their leverage whenever it is needed with low financing costs relative to market conditions. Thus, such firms are expected be more connected with capital markets. On the contrary, financially constrained firms tend to use less external finance relative to the unconstrained firms, and thus such firms are expected to be less exposed to uncertainties in capital markets. The overall picture of CCX to financially constrained firms (denoted as "C" henceforth) and unconstrained firms (denoted as "U" henceforth) are provided in Table 21. We find CCX is systematically greater for U than C across all subsamples, which is consistent with the above intuition. Furthermore, we assess how much is the CCX of U greater than CCX of C by taking the difference of CCX between U and C, and then divided by C for each subsample. We attribute the results to two points.

1. (U-C)/C is consistently larger during crisis periods than during stable period. It indicates that CCX increases more rapidly to U than C in times of crisis periods. That might mean some variables drive this result. We consider one of explanation on this point. We presume that greater cash holdings in financially constrained firms have stronger role in reducing CCX in turbulent times.
2. Our results show that UK has the largest (U-C)/C, followed by Euro-core countries. For example the subsample including UK firms during 2007-09 crisis presents the highest (U-C)/C of 1.13, indicating that CCX of U is two-fold to CCX of C. This result indicates that CCX trend is in different pattern for C and U, and it is especially more obvious for firms in UK and Euro-core countries and in times of crisis.

[INSERT TABLE 21 HERE]

The role of cash holdings should be important for C against U, because C tends to operate cashes as main financial strategy and choose to maintain higher cash reserves as a buffer against a possible cash flow shortfall in the future. On the other hand, U tends to use external funds as main financing tool, and thus the influence of cash holdings should be minor. Before jumping to the analysis of whether the positive effect of holding cash is stronger for financially constrained firms, we first look at whether financially constrained firms hold more cashes than financially unconstrained firms. Table 22 presents univariate comparisons of firms' cash holdings for subsamples based on financial constraints.[66]

[66] Almeida, Campello, and Weisbach (2004) provide evidence that firms with greater frictions in raising outside financing save a greater portion of their cash flow as cash than do those with fewer frictions. Financially constrained

As expected, for all classification criteria, the median and mean ratios of cash to total book assets are higher for financially constrained firms in the case of all countries. However, when separately looking at different regions, this rule is violated in Euro-periphery and Major Non-Euro countries, where we cannot observe cash holding is always greater for C across three classifications as we mark with bold face fonts. Therefore, it provides a clue that the cash holdings differently affecting C and U might be observe only in these two regions.

[INSERT TABLE 22 HERE]

We subsequently investigate whether the contribution of cash holdings to reduce CCX is greater for constrained firms. In Table 23, the interaction variable of $cashmta \times crisis\_dummy$ is negatively significant only for subsamples that include C firms. The role of cash holding is more pronounced for C firms in times of crisis, than U firms, which is consistent with our prediction 3 that cash holdings is more valuable to C firms when the credit market is crunch. The economic impact is quite huge. For example, during 2007-09 crisis, when focusing on the measure of financial constraints based on firms' size, the estimated coefficient along with cash is from -0.051 to -0.441 (-0.051+ -0.390) in the subsample including only financially constrained firms during the 2007-09 crisis, while it is from -0.798 to -1.099 (-0.798+ -0.301) in the subsample including only financially unconstrained firms. The economic impact on this analysis is from -0.4% to -3.7% for C, while from -5.5% to -7.3% for U.

We also find consistent pattern for other two alternative measures of financial constraints. For instance, based on firms' age, the estimated coefficient along with cash is from -0.133 to -0.548 (-0.133+-0.415) in the subsample with only C firms, while it is from -0.857 to -0.900 (-0.857+-0.043) in the subsample with only U firms. The economic impact is from -1.1% to -4.6% for the subsample with only C firms, while it is from -5.9% to -6.1% for the subsample with only U firms. Based on payout ratio, the estimated coefficient along with cash is from -0.272 to -0.978 (-0.272+-0.706) in the subsample with only C firms, while it is from -0.519 to -0.751 (-0.519+-0.232) in the subsample with only U firms. The economic impact is from -2.2% to -7.7% for the subsample with only C firms, while it is from -3.5% to -5.1% for the subsample with only U firms .

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firms (small, non-rated, low payout firms) may also want to hold more cash (Acharya, Almeida, and Campello, 2007) irrespective of competition to be able to realize investment opportunities because of their restricted access to cheap external funding.

Our results show that the coefficient of $cashmta \times crisis\_dummy$ is only negatively significant for constrained firms. We interpret these findings as consistent with the view that higher cash holdings of financially constrained firms are a risk-decreasing response to costly external financing.

[INSERT TABLE 23 HERE]

Our sample (Table 22) has presented that only for firms located in Euro-core countries and UK, constrained firms tend to reserve more cash than unconstrained firms based on the three classification of financial constraints. The results in Table 24 show that cash is risk-reducing, but this beneficial effect is restricted the regions of Euro-core and UK That is, the effect of cash holdings reducing CCX is only present in Euro-core and UK, but not in Euro-periphery and Non-euro (except UK). This result might give us some explanations why cash for financially constrained firms within Euro-periphery and Major non-Euro countries seems not to be as much important as those in Euro-core countries and UK.

Regarding to economic impact on this analysis in Euro-core countries, for example, during 2007-09 crisis, when focusing on the measure of financial constraints based on firms' size, the estimated coefficient along with cash is from 0.083 to -0.894 (0.083+ -0.977) in the subsample including only financially constrained firms during the 2007-09 crisis, while it is from -0.653 to -1.164 (-0.653+ -0.511) in the subsample including only financially unconstrained firms. The economic impact on this analysis is from 0.8% to -7.9% for C, while from -4.5% to -7.9% for U.

We also find consistent pattern for other two alternative measures of financial constraints. For instance, based on firms' age, the estimated coefficient along with cash is from -0.057 to -0.958 (-0.057+-0.901) in the subsample with only C firms, while it is from -0.569 to -0.876 (-0.569+-0.307) in the subsample with only U firms. The economic impact is from -0.5% to -8.3% for the subsample with only C firms, while it is from -4.1% to -6.3% for the subsample with only U firms .Based on payout ratio, the estimated coefficient along with cash is from -0.258 to -1.457 (-0.258+-1.199) in the subsample with only C firms, while it is from -0.309 to -0.463 (-0.309+-0.154) in the subsample with only U firms. The economic impact is from -2.2% to -11.9% for the subsample with only C firms, while it is from -2.3% to -3.4% for the subsample with only U firms.

Regarding to economic impact on this analysis in UK, for example, during 2007-09 crisis, when focusing on the measure of financial constraints based on firms' size, the estimated coefficient along with cash is from -0.213 to -1.328 (-0.213+ -1.115) in the subsample including only financially constrained firms during the 2007-09 crisis, while it is from -0.748 to -1.179 (-0.748+ -0.431) in the subsample including only financially unconstrained firms. The economic impact on this analysis is from 1.8% to -10.7% for C, while from -4.8% to -7.5% for U.

We also find consistent pattern for other two alternative measures of financial constraints. For instance, based on firms' age, the estimated coefficient along with cash is from 0.182 to -0.729 (0.182+-0.911) in the subsample with only C firms, while it is from -1.244 to -1.288 (-1.244+-0.044) in the subsample with only U firms. The economic impact is from 1.5% to -5.9% for the subsample with only C firms, while it is from -8.0% to -8.2% for the subsample with only U firms. Based on payout ratio, the estimated coefficient along with cash is from 0.048 to -0.818 (0.048+-0.886) in the subsample with only C firms, while it is from -1.142 to -1.478 (-1.142+-0.336) in the subsample with only U firms. The economic impact is from 0.4% to -6.3% for the subsample with only C firms, while it is from -6.5% to -8.3% for the subsample with only U firms.

Overall, across each model specification, we find that financially constrained firms (smaller firms, younger firms, and firms with lower payout ratios) are more likely to reduce the number of CCX because they hold more cashes in times of crisis, and these results are only present in Euro-core countries and UK. These results support our prediction 3 and suggest that financial condition proximity is also an important determinant of the number of conditional coexceedance between a firm and the financial sector.

[INSERT TABLE 24 HERE]

4.6. Robustness Tests

We consider a battery of robustness checks. First, we use global financial crisis and European debt crisis as crisis dummy to re-examine whether cash holdings is able to reduce CCX for constrained firms than for unconstrained firms, especially in times of crisis. Second, we apply this new crisis dummy to test the relation between CCX and cash holding in different region. Third, in order to avoid endogeneity problem, we measure financial constraints at the second quarter of 2006 to re-examine the relation between CCX and cashing holding. Fourth, we use new identification of financial constraint to test CCX and cash holding in different regions.

4.6.1. New crisis dummy: Financial constraint, Cash holding, CCX, and Different Regions

As a robustness test we adopt global financial crisis and European debt crisis as our crisis dummy. We re-examine the relationship between CCX and firms' cash holding in different criteria of financial constraint. Generally speaking, our main analysis remains the same (see Table 25). Next step, we re-test the cases based on different regions to see whether cashing holding could reduce CCX in accordance with criteria of financial constraint (see Table 26). The results here are similar as main analysis.

[INSERT TABLE 25 HERE]

[INSERT TABLE 26 HERE]

4.6.2. Endogeneity Concern: Financial constraint, Cash holding, and CCX

For our main analysis, we identify financial constrained firms every quarter and update every quarter (except for payout ratio, which is annual level measure). One would concern that there is an endogenous problem when re-identifying financially constrained firms during crisis period. In order to avoid this concern, we consider the other identification strategies by taking into account information one year before the onset of the mid-2007 subprime crisis.

We classify a firm as financially constrained firm based on the information on the end of second quarter of 2006. Then, we measure financial constraints at the second quarter of 2006, to avoid endogeneity concerns. We only consider firms with available data of size, age, or payout ratio at the end of June 2006. With this information, we identify constrained firms with value of size (age or payout ratio) lower than the median of size distribution at this time point. Because of doing this identification strategy, the full sample number of observations reduces to 87253 from 108139. Our results (see Table 27) do not change materially performing higher cash holdings of financially constrained firms are a risk-decreasing response to costly external financing.

[INSERT TABLE 27 HERE]

4.6.3 . Endogeneity Concern in different regions: Financial constraint, Cash holding, and CCX

Furthermore, we employ this new identification strategy of financial constraint in different regions. The results (see Table 28) still reveal financially constrained firms (smaller firms, younger firms, and firms with lower payout ratios) are more likely to reduce the number of CCX because they hold more cashes in times of crisis, and these results are only present in Euro-core countries and UK.

[INSERT TABLE 28 HERE]

4.7. Conclusion

It is generally accepted that the financial sector is more fragile than other sectors. Banks are more fragile than nonfinancial firms because of the inherent maturity mismatch on their balance sheet, which makes them vulnerable to bank runs. The banking sector interacts with the real economy, resulting in an additional mechanism that can amplify and propagate shocks hitting the financial sector.

In this paper, we find evidence that tail risk spillovers of financial sectors is mostly driven by episodes of negative firms' cash holding, past return, valuation, and distance to default, and is positive with firms' size, volatility, and leverage. Moreover, we compare the severity of CCX in different regions and results show tail risk spillover is stronger for Euro-periphery countries and less influence for UK. Besides, we aim to examine whether reserving cash is still valuable for financially constrained firms in that it enables firms to mitigate tail risks transmitted from the financial sector. Our empirical result has offered some evidence that cash provides important benefits to financially constrained firms in Euro-core countries and UK by reducing the tail risk spillover from distress financial sector in times of credit crunch. Overall, we establish the connection between firms' liquidity management (e.g., cash holdings), firms' financing conditions (e.g., financial constraints) and tail risks propagated from distressed financial sectors.

This paper is also somewhat related to the contagion literature. In times of financial crisis, investors and policy makers have a very strong interest in whether and how the crisis propagates to non-financial firms; this is known as contagion effects. In this paper, we investigate the interaction effects in the developed European markets. Our analysis provides valuable information about the typical market conditions and dynamics. Furthermore our results add to the growing body of literature supporting the financial sector risk's role as a leading indicator of real economy overall risk and specially tail risk. Our results may also help financial regulators trying to evaluate the true overall economic cost of financial crises.

Appendix

A.1 Explanation of variables

Variable	Definition
Volatility	Annualized standard deviation of daily stock returns.
Distance to Default	Standard deviation of a firm's value away from its default point, computed based on Merton model
Growth Opportunity	Logarithm of market equity scaled by book equity
Return	Sum of daily returns over a quarter.
Cash Holding	Cash and equivalents scaled by firm market equity plus total liability
Firm Size	Logarithm of book value of total assets in U.S. dollar
Leverage	Total liability scaled by firm market equity plus total liability

A.2 The correlation among three criteria of financial constraint

	size	age	Payout ratio
size	1.00	0.33	0.22
age	0.33	1.00	0.15
Payout ratio	0.22	0.15	1.00

CHAPTER 5

Final Remarks

In this dissertation, we investigate the connection between industry structural constraints and firms' failure prediction based on two dimensions: (1) the intensity of industry concentration, and (2) the degree of dependence on customers and suppliers. The key results are: (i) failure and bankruptcy probabilities increase when the degree of competition in a given industry decreases., (ii) the probability of bankruptcy is higher for firms in industries with relatively stronger customer dependency but this factor does not affect failure probabilities.

Also, we propose a new approach to measure tail risk spillovers from one economic sector to other sectors: the CCX. We apply this approach to the financial sector and real economy industries in the United States from 2001 to 2011. We find large volatility and tail risk spillovers from the financial sector to many real economy sectors during this period. These spillovers are even stronger during the 2007–2009 financial crisis. In addition, we find evidence suggesting that the higher the degree of competition, the stronger these tail risk spillovers. Three industry characteristics help explain the size of tail spillovers. The net debt financing has a positive effect on the size, whereas valuation and investment have a negative impact.

Finally, we find evidence that tail risk spillovers of financial sectors is mostly driven by episodes of negative firms' cash holding, past return, valuation, and distance to default, and is positive with firms' size, volatility, and leverage. Moreover, we compare the severity of CCX in different regions and results show tail risk spillover is stronger for Euro-periphery countries and less influence for UK. Besides, we aim to examine whether reserving cash is still valuable for financially constrained firms in that it enables firms to mitigate tail risks transmitted from the financial sector. The empirical result has offered some evidence that cash provides important benefits to financially constrained firms in Euro-core countries and UK by reducing the tail risk spillover from distress financial sector in times of credit crunch. Overall, we establish the connection between firms' liquidity management (e.g., cash holdings), firms' financing conditions (e.g., financial constraints) and tail risks prorogated from distressed financial sectors.

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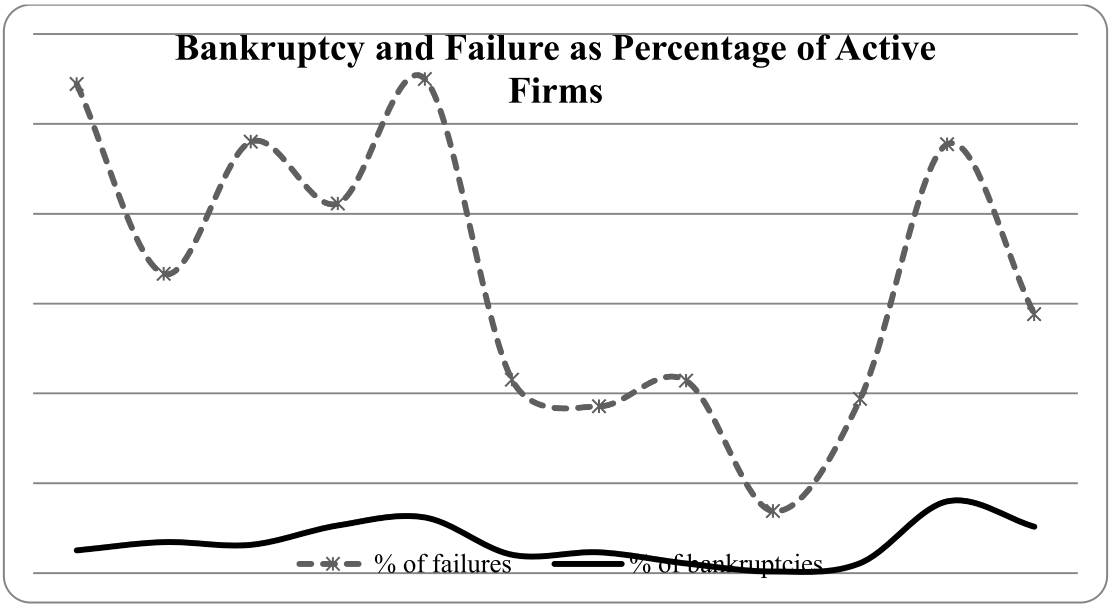


Figure 1. Bankruptcy and Failure by Year. Bankruptcy (Failure) must satisfy two conditions: (1) Firms have been listed in the NYSE, AMEX, or NASDAQ exchange during 1998–2008 and (2) their reported delisting code in CRSP is 400, 572, or 574 (400 or 550–585). There are 247 bankruptcies and 2496 failures in the sample.

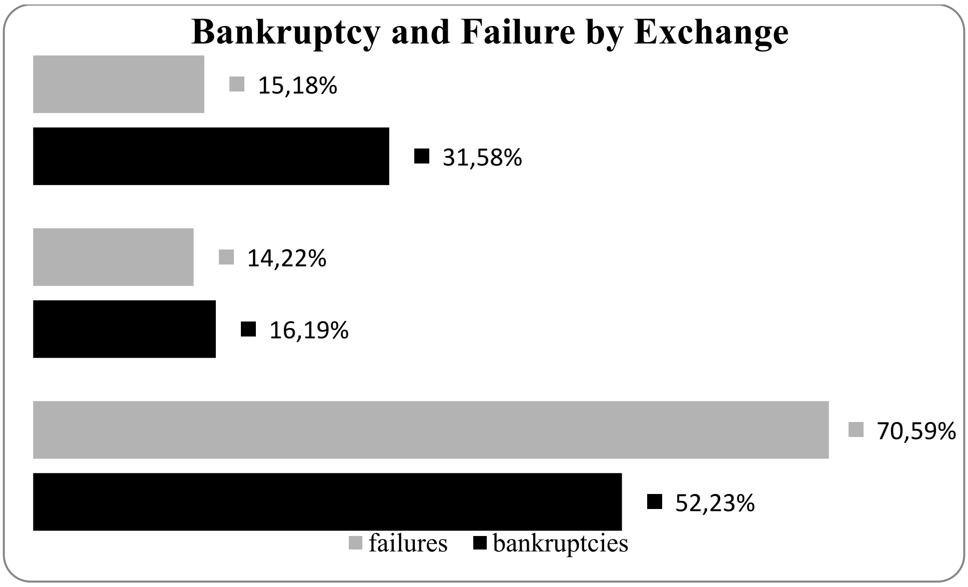
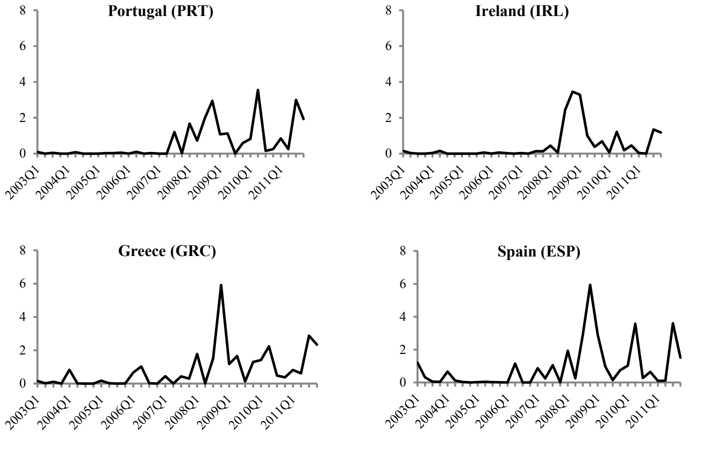
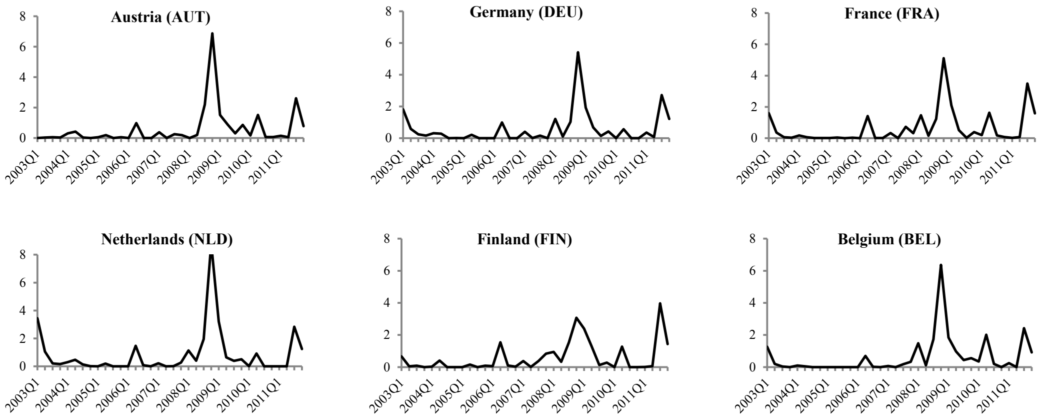


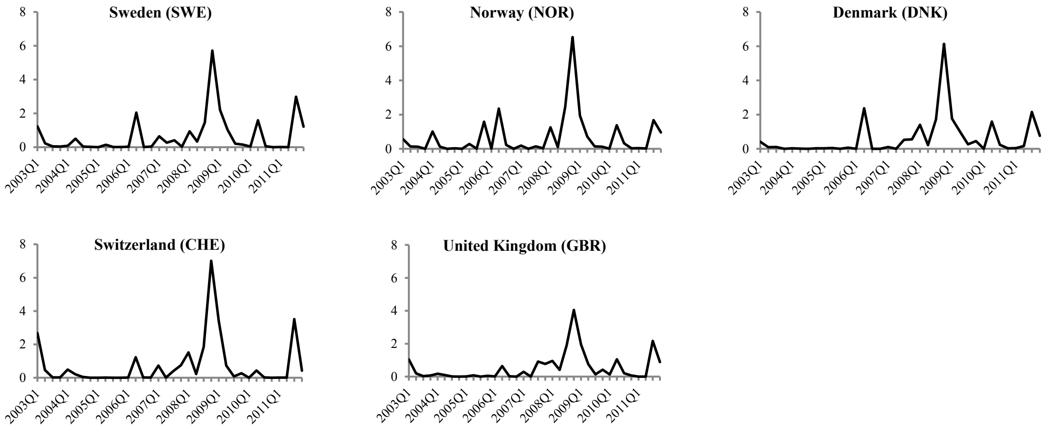
Figure 2. Bankruptcy and Failure by Exchange. Bankruptcy (Failure) must satisfy two conditions: (1) Firms have been listed in the NYSE, AMEX, or NASDAQ exchange during 1998–2008 and (2) their reported delisting code in CRSP is 400, 572, or 574 (400 or 550–585). The 247 bankruptcies (black bars) and the 2496 failures (gray bars) in the sample are separated by exchange in this table, along with the percentages of the total number of bankruptcies (failures).



Panel A: Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain)



Panel B: Euro-core countries (Austria, Germany, France, the Netherlands, Finland, Belgium)



Panel C: Major non-euro zone countries (Sweden, Norway, Denmark, Switzerland) and UK

Figure 3. **CCX measures of countries**. This figure plots CCX measure of 16 European countries during 2003-2011, by different regions. The Panel A, B, and C stand for Euro-periphery countries, Euro-core countries, and Major non-euro zone countries and UK.

Table 1. Bankruptcy and Failure by IOCode. Bankruptcy (Failure) must satisfy three conditions: (1) Firms have been listed in the NYSE, AMEX, or NASDAQ exchange during 1998 to 2009; (2) their reported delisting code in CRSP is 400 or 550–585 (400 or 550–585); and (3) this NAICS code mirrors an IOCode in the conversion table. The 247 bankruptcies and 2496 failures are listed by IOCode. The industry classification system of Input-Output Sector table identifies fourteen industries after 1998.

IOCode	Industry	Bankruptcy	Failure
11	Agriculture, forestry, fishing and hunting	0	6
21	Mining	9	106
22	Utilities	5	17
23	Construction	6	46
31G	Manufacturing	96	965
42	Wholesale trade	8	107
44RT	Retail trade	24	110
48TW	Transportation and warehousing	8	54
51	Information	33	408
FIRE	Finance, insurance, real estate, rental, and leasing	31	311
PROF	Professional and business services	12	209
6	Educational services, health care, and social assistance	7	60
7	Arts, entertainment, recreation, accommodation, and food services	8	84
81	Other services, except government	0	13
	Total	247	2496

Table 2. Summary Statistics. This table offers summary statistics of the independent variables for the sample period 1998–2009. The databases are COMPUSTAT and CRSP. There are 12031 firms and 72945 observations in the yearly sample. The variable definitions are: (1) EXRET = the sum of monthly excess return over the value-weighted NYSE/AMEX/NASDAQ return for past 12 months; (2) RSIZ = relative size, measured as the log of the firm's market capitalization divided by total NYSE/AMEX/NASDAQ market capitalization; (3) SIGMA =the annualized standard deviation of residuals from the regression of each stock's monthly returns on the monthly value-weighted NYSE/AMEX/NASDAQ index return over past twelve months; (4) NI/TA = net income/total assets; (5) TL/TA = total liabilities/total assets; (6) CASH/TA = ratio of a company's cash and short-term assets to its total assets; (7) *HHI* = Herfindahl index on sales; (8) $C_{i,C}$ = direct customer constraint; (9) $C_{i,S}$ = direct supplier constraint; (10) $IC_{i,C}$=indirect customer constraint; (11) $IC_{i,S}$ = indirect supplier constraint. Panels B and C provide summary statistics on bankruptcy and failure observations respectively.

Variable	EXRET	RSIZ	SIGMA	NI/TA	TL/TA	CASH/TA	*HHI*	$C_{i,C}$	$C_{i,S}$	$IC_{i,C}$	$IC_{i,C}$
Panel A: All firm-year observations over 1998–2009 (72945 observations)											
MEDIAN	0,016	-11,179	0,379	0,017	0,536	0,081	0,187	0,017	0,025	0,017	0,022
MEAN	0,050	-11,101	0,474	-0,047	0,539	0,182	0,282	0,018	0,025	0,018	0,023
MIN	-1,391	-15,235	0,090	-1,309	0,034	0,000	0,026	0,011	0,008	0,015	0,021
MAX	1,874	-5,92	1,789	0,277	1,216	0,887	1,000	0,042	0,034	0,021	0,026
STD	0,563	2,054	0,333	0,251	0,273	0,223	0,262	0,004	0,006	0,001	0,001
Panel B: Bankrupt firm-year observations over 1998–2009 (247 observations)											
MEDIAN	-0,674	-12,862	0,724	-0,093	0,774	0,049	0,264	0,019	0,025	0,018	0,023
MEAN	-0,581	-12,669	0,805	-0,227	0,756	0,122	0,383	0,019	0,025	0,018	0,023
STD	0,663	1,717	0,385	0,350	0,271	0,187	0,307	0,006	0,006	0,001	0,001
Panel C: Failure firm-year observations over 1998–2009 (2496 observations)											
MEDIAN	-0,484	-13,838	0,750	-0,156	0,659	0,075	0,231	0,018	0,025	0,018	0,023
MEAN	-0,403	-13,590	0,830	-0,338	0,643	0,180	0,342	0,018	0,025	0,018	0,023
STD	0,774	1,441	0,421	0,432	0,301	0,230	0,290	0,005	0,006	0,001	0,001

Table 3. Correlation matrix

Independent Variables	*EXERT*	*RSIZ*	*SIGMA*	*NI/TA*	*TL/TA*	*CASH/TA*	*HHI*	$C_{i,C}$	$C_{i,S}$	$IC_{i,C}$	$IC_{i,S}$
EXERT	1,000	0,163	0,279	0,039	-0,033	0,056	-0,005	0,025	-0,017	0,083	0,048
RSIZ		1,000	-0,354	0,303	0,069	-0,097	-0,053	0,014	0,005	0,013	-0,070
SIGMA			1,000	-0,448	-0,146	0,263	0,035	0,038	-0,061	0,086	0,196
NI/TA				1,000	0,002	-0,321	0,060	0,020	0,027	-0,076	-0,072
TL/TA					1,000	-0,470	-0,084	0,038	0,221	0,003	-0,075
CASH/TA						1,000	-0,098	-0,044	-0,087	0,015	0,003
HHI							1,000	-0,013	-0,202	0,010	0,073
$C_{i,C}$								1,000	0,455	-0,003	0,093
$C_{i,S}$									1,000	0,024	-0,098
$IC_{i,C}$										1,000	0,677
$IC_{i,S}$											1,000

Table 4. Logit Regressions of Bankruptcy Indicators on Predictor Variables. The table reports results from logit regressions of bankruptcies on predictors. The estimates include firms traded on the NYSE, AMEX, and NASDAQ with yearly observations from 1998 to 2009. Model 1 is the benchmark model including EXRET, RSIZ, SIGMA, NI/TA, TL/TA CASH/TA. Model 2 additionally includes the internal industry constraint (*HHI*). Model 3 expands Model 2 by including the direct external industry constrains ($C_{i,c}$ and $C_{i,S}$). The indirect external industry constraints are added into Model 4. Parameter estimates are given first followed by chi-square values in brackets.*Significant at 10%, **Significant at 5%, ***Significant at 1%. The -2LOG(LF) and McFadden-R^2 is also reported in Panel A. In Panel B, the CHI-SQUARE is the difference of -2LOG(LF) in Model 1 and other Models, and its corresponding P-VALUE.

	Model 1	Model 2	Model 3	Model 4
Panel A: Estimation using 1998–2009 data				
Constant	-9,6531***(363,56)	-9,8942***(380,04)	-10,3457***(312,31)	-11,2965***(68,85)
EXRET	-1,6835***(232,11)	-1,6773***(230,76)	-1,6923***(234,18)	-1,7218***(238,69)
RSIZ	-0,0665*(2,73)	-0,0553(1,9)	-0,0557(1,93)	-0,0675*(2,81)
SIGMA	2,3540***(178,52)	2,2976***(165,43)	2,2706***(158,95)	2,2260***(148,76)
NI/TA	0,29(1,93)	0,2413(1,34)	0,2468(1,38)	0,2648(1,57)
TL/TA	2,4485***(95,19)	2,5138***(99,79)	2,6003***(103,2)	2,5339***(96,41)
CASH/TA	-1,0164**(5,83)	-0,7798*(3,42)	-0,6758(2,57)	-0,7203*(2,87)
Internal industry constraint				
HHI		1,0093***(22,85)	0,9812***(20,33)	0,9978***(21,17)
Direct external constraint				
$C_{i,C}$			53,8940***(20,96)	65,3657***(26,11)
$C_{i,S}$			-23,7828**(3,99)	-32,6557***(6,83)
Indirect external constraint				
$IC_{i,C}$				215,3000***(9,85)
$IC_{i,S}$				-127,6*(2,85)
# of observations	72945	72945	72945	72945
# of bankruptcies or failures	247	247	247	247
-2LOG(LF)	2620,05	2598,93	2581,47	2571,25
Pseudo-R^2	0,2068	0,2132	0,2185	0,2216
Panel B: Are industry constraint variables significant?				
CHI-SQUARE		21,12	38,58	48,80
P-VALUE		0	0	0

Table 5. Logit Regressions of Failure Indicators on Predictor Variables. The table reports results from logit regressions of failures on predictors. The estimates include firms traded on the NYSE, AMEX, and NASDAQ with yearly observations from 1998 to 2009. Model 1 is the benchmark model including the controls EXRET, RSIZ, SIGMA, NI/TA, TL/TA CASH/TA. Model 2 additionally includes the internal industry constraint (*H*). Model 3 expands Model 2 by including direct external industry constrains ($C_{i,C}$ and $C_{i,S}$). The indirect external industry constraints are added into Model 4. Parameter estimates are given first followed by chi-square values in brackets.*Significant at 10%, **Significant at 5%, ***Significant at 1%. The -2LOG(LF) and McFadden-R^2 is also reported in Panel A. In Panel B, the CHI-SQUARE is the difference of -2LOG(LF) in Model 1 and other Models, and its corresponding P-VALUE.

Panel A: Estimation using 1998–2009 data

	Model 1	Model 2	Model 3	Model 4
Constant	-13,1574***(3024,11)	-13,2543***(3071,41)	-13,3622***(2594,09)	-15,9314***(926,49)
EXRET	-1,0760***(873,92)	-1,0771***(872,93)	-1,0768***(872,49)	-1,0674***(851,13)
RSIZ	-0,6156***(1246,89)	-0,6049***(1204,76)	-0,6049***(1204,89)	-0,6010***(1186,29)
SIGMA	1,7701***(757,35)	1,7496***(731,91)	1,7476***(727,33)	1,7040***(678,27)
NI/TA	-0,7415***(121,08)	-0,7703***(129,77)	-0,7741***(130,49)	-0,7680***(127,53)
TL/TA	1,4822***(291,63)	1,5325***(308,77)	1,5246***(299,59)	1,5727***(314,34)
CASH/TA	-0,4393***(5,83)	-0,3185**(6,62)	-0,3162**(6,5)	-0,2517**(4,0893)
Internal industry constraint				
HHI		0,6146***(56,74)	0,6234***(56,84)	0,6187***(55,89)
Direct external constraint				
$C_{i,C}$			3,3028(0,34)	-3,1863(0,30)
$C_{i,S}$			1,9816(0,22)	8,7005**(3,88)
Indirect external constraint				
$IC_{i,C}$				-51,5095**(3,99)
$IC_{i,S}$				151,3000***(31,38)
# of observations	72945	72945	72945	72945
# of bankruptcies or failures	2496	2496	2496	2496
-2LOG(LF)	14779,7	14725	14724	14685,8
Pseudo-R^2	0,3206	0,3231	0,3232	0,3249

Panel B: Are industry constraint variables significant?

	Model 1	Model 2	Model 3	Model 4
CHI-SQUARE		54,7	55,7	93,9
P-VALUE		0	0	0

Table 6. Additional Test on Concentration Ratios. The table reports estimated coefficients on alternative concentration measures from logit regressions of bankruptcies or failures on EXRET, RSIZ, SIGMA, NI/TA, TL/TA CASH/TA, and alternative measures of concentration. *HHI* is Herfindahl index computed by sales data in COMPUSTAT. *CR4* is the four-firm concentration ratio collected from the census published in BEA. Dummy(0,4), Dummy(0,5), and Dummy(Medium) are a dummy variables that equal to 0 if *HHI* (In panel A) or *CR4* (In panel B) is below 0,4, 0,5, and its medium respectively; otherwise is equal to 1. Parameter estimates are given followed by chi-square values in brackets.*Significant at 10%, **Significant at 5%, ***Significant at 1%.

Dependent variable:	Bankruptcy				Failure			
Sample Period:	1990–2009		1998–2009		1990–2009		1998–2009	
Panel A: COMPUSATAT concentration ratio								
HHI	0,8093***	(22,1441)	0,9955***	(22,3663)	0,4717***	(55,8949)	0,5854***	(52,2973)
Dummy(0,4)	0,4957***	(20,8203)	0,5855***	(18,5000)	0,2503***	(41,2667)	0,3112***	(37,2694)
Dummy(0,5)	0,4829***	(17,5751)	0,5777***	(16,2795)	0,2427***	(33,0697)	0,3324***	(36,9556)
Dummy(Medium)	0,4101***	(13,9709)	0,5549***	(16,1586)	0,2146***	(33,8131)	0,2380***	(25,8882)
# of observations	123304		73558		123304		73558	
# of bankruptcy or failure	385		251		4104		2581	
Panel B: Census concentration ratio								
CR4	1,2644***	(13,8302)	0,7851**	(4,0550)	0,2022*	(2,7845)	0,2315	(2,5378)
Dummy(0,4)	0,5349***	(17,9102)	0,4302***	(9,1160)	0,1151***	(6,6848)	0,1443***	(7,6156)
Dummy(0,5)	0,3836**	(6,3696)	0,3522**	(4,5897)	0,0711	(1,5629)	0,0807	(1,5651)
Dummy(Medium)	0,5898***	(20,4328)	0,3740***	(6,3129)	0,0613	(2,1312)	0,0743	(2,1210)
# of observations	98703		65539		98703		65539	
# of bankruptcy or failure	273		215		3109		2163	

Table 7

Descriptive statistics of industry-level returns over the full sample period.

Industry Name	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	p-Value	# of firms[a]
Crop Production	0.001	0.001	0.188	-0.155	0.021	0.246	11.286	7942.86	0	9.96
Animal Production and Aquaculture	0	0.001	0.129	-0.149	0.021	-0.452	11.014	7497.95	0	2.59
Forestry and Logging	0.001	0	0.241	-0.146	0.021	0.96	17.413	24375.91	0	2.60
Oil and Gas Extraction	0.001	0.002	0.206	-0.166	0.022	-0.174	12.055	9466.69	0	138.83
Mining (except Oil and Gas)	0.001	0.002	0.209	-0.135	0.023	0.117	9.867	5442.66	0	95.45
Support Activities for Mining	0.001	0.001	0.23	-0.176	0.025	-0.209	9.041	4227.18	0	35.93
Utilities	0.001	0.001	0.147	-0.086	0.013	0.454	16.244	20316.47	0	131.36
Construction of Buildings	0.001	0	0.16	-0.126	0.026	0.196	5.595	794.36	0	25.41
Heavy and Civil Engineering Construction	0.001	0.001	0.139	-0.176	0.023	-0.242	7.916	2813.71	0	25.02
Specialty Trade Contractors	0.001	0.002	0.19	-0.142	0.024	-0.046	10.163	5916.09	0	11.99
Food Manufacturing	0	0.001	0.093	-0.069	0.01	0.141	11.607	8549.41	0	74.57
Beverage and Tobacco Product Manufacturing	0.001	0.001	0.112	-0.084	0.011	-0.14	10.695	6835.27	0	40.76
Textile Mills	0.001	0.001	0.178	-0.13	0.021	0.174	8.811	3907.22	0	8.48
Textile Product Mills	0.001	0	0.285	-0.126	0.024	0.838	13.183	12277.96	0	4.09
Apparel Manufacturing	0.001	0.001	0.122	-0.093	0.017	0.078	7.028	1873.62	0	42.63
Leather and Allied Product Manufacturing	0.001	0.001	0.13	-0.118	0.017	0.134	8.439	3418.76	0	20.45
Wood Product Manufacturing	0.001	0.001	0.126	-0.154	0.021	-0.082	7.609	2451.83	0	18.53
Paper Manufacturing	0	0.001	0.087	-0.097	0.014	-0.119	7.835	2701.93	0	39.85
Printing and Related Support Activities	0.001	0.001	0.142	-0.113	0.019	0.156	10.64	6741.57	0	19.40
Petroleum and Coal Products Manufacturing	0.001	0.001	0.177	-0.136	0.017	0.168	14.5	15259.19	0	36.56
Chemical Manufacturing	0	0.001	0.109	-0.067	0.012	0.055	9.63	5069.22	0	474.89
Plastics and Rubber Products Manufacturing	0.001	0.001	0.101	-0.109	0.017	-0.058	6.889	1745.08	0	36.63
Nonmetallic Mineral Product Manufacturing	0.001	0.001	0.145	-0.119	0.022	0.172	8.508	3510.92	0	21.19
Primary Metal Manufacturing	0.001	0.001	0.247	-0.179	0.026	0.055	11.86	9051.77	0	56.57
Fabricated Metal Product Manufacturing	0.001	0.001	0.104	-0.097	0.016	-0.019	7.582	2420.51	0	58.73
Machinery Manufacturing	0.001	0.001	0.138	-0.117	0.019	0.03	7.525	2361.32	0	169.01
Computer and Electronic Product Manufacturing	0.001	0.001	0.171	-0.086	0.02	0.502	8.351	3416.61	0	627.70
Electrical Equipment, Appliance, and Component Manufacturing	0.001	0.001	0.138	-0.124	0.018	0.039	8.485	3468.93	0	82.71
Transportation Equipment Manufacturing	0.001	0.001	0.125	-0.115	0.016	-0.117	8.858	3963.19	0	107.14
Furniture and Related Product Manufacturing	0.001	0.001	0.12	-0.112	0.019	0.132	7.91	2787.63	0	24.58
Miscellaneous Manufacturing	0.001	0.001	0.119	-0.072	0.012	-0.054	10.297	6139.63	0	135.39
Merchant Wholesalers, Durable Goods	0.001	0.001	0.086	-0.088	0.015	-0.021	6.516	1425.62	0	88.63
Merchant Wholesalers, Nondurable Goods	0.001	0.001	0.123	-0.085	0.013	-0.046	10.934	7258.44	0	53.74
Wholesale Electronic Markets and Agents and Brokers	0.001	0	0.176	-0.268	0.023	-0.459	20.265	34461.76	0	2.26
Motor Vehicle and Parts Dealers	0.001	0.001	0.116	-0.097	0.017	0.458	7.968	2941.8	0	19.26
Furniture and Home Furnishings Stores	0.001	0	0.209	-0.115	0.022	0.753	9.057	4491.15	0	7.72
Electronics and Appliance Stores	0.001	0.001	0.167	-0.171	0.023	0.171	8.406	3382.49	0	10.18
Building Material and Garden Equipment and Supplies Dealers	0	0	0.15	-0.108	0.02	0.476	7.902	2874.39	0	5.03
Food and Beverage Stores	0	0	0.08	-0.089	0.015	-0.354	6.518	1484.35	0	21.20
Health and Personal Care Stores	0	0	0.133	-0.092	0.015	-0.05	9.232	4478.15	0	14.15
Gasoline Stations	0.001	0.001	0.188	-0.163	0.021	0.348	9.669	5182.87	0	4.33
Clothing and Clothing Accessories Stores	0.001	0.001	0.133	-0.121	0.019	0.183	6.95	1814.42	0	54.32
Sporting Goods, Hobby, Musical Instrument, and Book Stores	0.001	0.001	0.124	-0.101	0.02	0.322	6.593	1536.61	0	17.31

General Merchandise Stores	0	0	0.118	-0.083	0.014	0.371	7.766	2682.41	0	25.15
Miscellaneous Store Retailers	0.001	0	0.166	-0.12	0.021	0.537	8.688	3862.57	0	13.11
Nonstore Retailers	0.002	0.001	0.195	-0.114	0.023	0.766	10.045	5992.94	0	33.25
Air Transportation	0.001	0	0.162	-0.311	0.025	-0.322	13.839	13591.9	0	28.28
Rail Transportation	0.001	0.001	0.111	-0.107	0.018	-0.043	6.381	1318.74	0	12.97
Water Transportation	0.001	0.001	0.15	-0.25	0.021	-0.638	15.011	16819.24	0	37.40
Truck Transportation	0.001	0	0.105	-0.116	0.02	0.108	5.561	761.31	0	24.79
Pipeline Transportation	0.001	0.001	0.212	-0.1	0.015	0.374	22.74	44990.19	0	21.81
Support Activities for Transportation	0.001	0.001	0.102	-0.101	0.018	0.04	6.229	1202.96	0	13.80
Couriers and Messengers	0	0	0.079	-0.097	0.016	0.07	7.083	1924.53	0	8.35
Warehousing and Storage	0.001	0.001	0.131	-0.108	0.014	0.26	14.762	15982.18	0	3.08
Publishing Industries (except Internet)	0.001	0	0.152	-0.085	0.018	0.535	9.678	5273.83	0	273.65
Motion Picture and Sound Recording Industries	0.001	0	0.108	-0.092	0.017	0.214	7.172	2028.13	0	18.94
Broadcasting (except Internet)	0	0	0.154	-0.12	0.019	0.271	10.356	6271.68	0	63.26
Telecommunications	0.001	0.001	0.142	-0.086	0.015	0.443	11.054	7570.13	0	156.64
Data Processing, Hosting, and Related Services	0.001	0.001	0.114	-0.098	0.014	0.139	8.429	3406.36	0	44.25
Other Information Services	0.001	0.001	0.162	-0.118	0.022	0.373	6.943	1856.62	0	53.81
Professional, Scientific, and Technical Services	0.001	0.001	0.103	-0.072	0.015	0.277	7.802	2693.74	0	248.67
Administrative and Support Services	0.001	0.001	0.095	-0.094	0.016	0.04	7.042	1884.53	0	85.91
Waste Management and Remediation Services	0.001	0.001	0.151	-0.096	0.015	0.149	10.265	6094.81	0	19.46
Educational Services	0.001	0.001	0.104	-0.13	0.018	-0.167	7.331	2175.22	0	22.45
Ambulatory Health Care Services	0.001	0.002	0.125	-0.148	0.017	-0.755	11.155	7929.94	0	32.16
Hospitals	0.001	0.001	0.231	-0.251	0.028	0.064	13.016	11569.13	0	5.48
Nursing and Residential Care Facilities	0.001	0.001	0.42	-0.235	0.028	1.906	49.086	246548.2	0	7.36
Performing Arts, Spectator Sports, and Related Industries	0	0	0.132	-0.113	0.018	-0.017	9.035	4198.78	0	7.43
Amusement, Gambling, and Recreation Industries	0.001	0.001	0.146	-0.132	0.02	0.237	9.939	5577.67	0	21.81
Accommodation	0.001	0.001	0.234	-0.199	0.026	0.322	11.849	9074.63	0	29.55
Food Services and Drinking Places	0.001	0.001	0.093	-0.082	0.013	0.049	6.182	1168.22	0	67.25
Repair and Maintenance	0.001	0	0.096	-0.117	0.021	0.148	5.06	499.36	0	2.91
Personal and Laundry Services	0.001	0.001	0.168	-0.104	0.016	0.356	10.866	7192.03	0	14.85
Finance	0.001	0.001	0.149	-0.13	0.019	0.482	13.813	13588.04	0	1796.00

Notes: This table presents descriptive statistics of the daily returns for each industry during the full sample period of 2001–2011, totaling 2767 daily observations for each industry.

[a] The average number of firms that are contained in each industry.

Table 8

Descriptive statistics of industry-level returns during crisis period.

Industry Name	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	p-Value	# of firms[a]
Crop Production	0.001	0.002	0.188	-0.155	0.037	0.293	6.821	274.612	0	7.58
Animal Production and Aquaculture	0	0	0.093	-0.149	0.023	-1.152	12.127	1628.216	0	2.71
Forestry and Logging	0	0	0.241	-0.146	0.040	0.988	8.414	610.327	0	2.00
Oil and Gas Extraction	0	0.003	0.206	-0.166	0.037	-0.023	7.880	437.618	0	157.99
Mining (except Oil and Gas)	0.001	0.002	0.209	-0.135	0.038	0.274	6.496	230.041	0	111.47
Support Activities for Mining	-0.001	0.001	0.230	-0.176	0.038	-0.153	8.547	567.016	0	37.89
Utilities	0	0.001	0.147	-0.086	0.021	0.939	11.791	1484.998	0	126.24
Construction of Buildings	0	-0.001	0.160	-0.126	0.040	0.264	3.955	21.888	0	25.83
Heavy and Civil Engineering Construction	-0.001	0	0.139	-0.176	0.036	-0.296	6.278	203.842	0	26.76
Specialty Trade Contractors	0	0	0.190	-0.142	0.039	0.146	6.581	237.244	0	13.74
Food Manufacturing	0	0	0.093	-0.069	0.016	0.532	8.970	675.805	0	70.46
Beverage and Tobacco Product Manufacturing	0	0	0.112	-0.078	0.015	0.403	12.55	1687.734	0	38.24
Textile Mills	-0.002	-0.001	0.105	-0.130	0.027	-0.140	5.739	139.329	0	6.07
Textile Product Mills	-0.002	-0.004	0.163	-0.126	0.034	0.434	5.655	143.380	0	4.00
Apparel Manufacturing	-0.001	-0.002	0.122	-0.093	0.027	0.188	4.729	57.546	0	38.68
Leather and Allied Product Manufacturing	-0.001	-0.001	0.130	-0.118	0.028	0.340	5.340	109.078	0	17.08
Wood Product Manufacturing	-0.001	0.001	0.126	-0.154	0.033	-0.074	5.289	96.669	0	17.01
Paper Manufacturing	-0.001	0	0.087	-0.097	0.020	-0.029	6.373	209.157	0	34.42
Printing and Related Support Activities	-0.002	-0.001	0.142	-0.113	0.031	0.384	6.015	177.797	0	14.49
Petroleum and Coal Products Manufacturing	0	0.002	0.177	-0.136	0.028	0.397	9.774	854.685	0	34.98
Chemical Manufacturing	0	0.001	0.109	-0.067	0.017	0.319	9.306	738.218	0	494.76
Plastics and Rubber Products Manufacturing	-0.001	-0.002	0.086	-0.109	0.027	-0.048	4.361	34.198	0	26.22
Nonmetallic Mineral Product Manufacturing	-0.001	-0.001	0.145	-0.119	0.034	0.327	5.667	138.526	0	19.01
Primary Metal Manufacturing	-0.001	0	0.247	-0.179	0.045	0.201	7.032	301.744	0	48.76
Fabricated Metal Product Manufacturing	-0.001	0	0.104	-0.097	0.025	0.007	4.853	63.108	0	51.85
Machinery Manufacturing	-0.001	0.001	0.138	-0.117	0.029	-0.030	6.178	185.699	0	149.11
Computer and Electronic Product Manufacturing	0	0.001	0.118	-0.086	0.023	0.268	5.860	155.607	0	598.00
Electrical Equipment, Appliance, and Component Manufacturing	-0.001	0	0.138	-0.124	0.028	0.107	6.403	213.63	0	79.67
Transportation Equipment Manufacturing	-0.001	0	0.125	-0.093	0.025	0.227	6.469	224.951	0	101.92
Furniture and Related Product Manufacturing	-0.001	-0.001	0.120	-0.112	0.031	0.290	4.759	63.039	0	20.45
Miscellaneous Manufacturing	0	0	0.119	-0.072	0.018	0.136	9.425	759.924	0	125.51
Merchant Wholesalers, Durable Goods	0	0.001	0.086	-0.088	0.023	-0.110	4.885	66.179	0	79.39
Merchant Wholesalers, Nondurable Goods	-0.001	0	0.123	-0.078	0.020	0.300	9.148	701.022	0	51.40
Wholesale Electronic Markets and Agents and Brokers	0	-0.001	0.128	-0.106	0.024	0.151	6.666	248.579	0	2.00
Motor Vehicle and Parts Dealers	0	-0.002	0.116	-0.084	0.027	0.514	4.863	83.194	0	17.66
Furniture and Home Furnishings Stores	0	-0.002	0.140	-0.103	0.031	0.620	4.905	94.893	0	7.55
Electronics and Appliance Stores	0	0	0.149	-0.098	0.030	0.541	6.040	191.355	0	8.14
Building Material and Garden Equipment and Supplies Dealers	-0.001	-0.003	0.150	-0.084	0.029	0.717	5.209	127.394	0	4.47
Food and Beverage Stores	-0.001	-0.001	0.080	-0.085	0.021	-0.021	4.614	47.902	0	15.05
Health and Personal Care Stores	0	-0.001	0.133	-0.092	0.021	0.424	9.217	723.419	0	13.08
Gasoline Stations	0	0.001	0.188	-0.140	0.029	0.675	9.686	854.968	0	5.42
Clothing and Clothing Accessories Stores	0	-0.002	0.117	-0.099	0.029	0.228	4.300	34.881	0	53.05

Sporting Goods, Hobby, Musical Instrument, and Book Stores	-0.001	-0.003	0.112	-0.101	0.032	0.386	4.199	37.356	0	16.16
General Merchandise Stores	0	-0.001	0.117	-0.083	0.021	0.425	6.230	204.948	0	20.03
Miscellaneous Store Retailers	-0.001	-0.003	0.139	-0.120	0.031	0.567	5.680	155.645	0	12.26
Nonstore Retailers	0	-0.002	0.126	-0.114	0.031	0.478	5.562	137.404	0	31.30
Air Transportation	0	-0.001	0.162	-0.116	0.039	0.428	4.446	51.870	0	28.27
Rail Transportation	0	0.001	0.094	-0.107	0.027	-0.124	4.426	38.506	0	10.04
Water Transportation	-0.001	-0.001	0.150	-0.113	0.032	0.104	5.441	110.309	0	46.86
Truck Transportation	0	-0.002	0.105	-0.116	0.029	0.118	4.270	30.656	0	21.45
Pipeline Transportation	0	0	0.212	-0.100	0.023	1.313	21.13	6166.848	0	26.41
Support Activities for Transportation	0	0	0.102	-0.101	0.027	0.097	4.752	57.076	0	15.20
Couriers and Messengers	-0.001	-0.002	0.079	-0.097	0.024	0.108	5.122	83.641	0	7.54
Warehousing and Storage	0	0	0.131	-0.108	0.024	0.224	9.135	695.178	0	2.83
Publishing Industries (except Internet)	0	-0.001	0.152	-0.085	0.024	0.627	8.071	501.349	0	211.78
Motion Picture and Sound Recording Industries	-0.001	-0.002	0.108	-0.09	0.024	0.299	5.544	125.494	0	16.42
Broadcasting (except Internet)	-0.001	-0.001	0.154	-0.111	0.027	0.584	8.941	673.678	0	62.17
Telecommunications	0	0	0.142	-0.086	0.023	0.717	8.792	654.228	0	145.73
Data Processing, Hosting, and Related Services	0	0	0.114	-0.086	0.020	0.232	7.451	368.014	0	30.63
Other Information Services	0	-0.001	0.135	-0.106	0.026	0.483	6.786	280.492	0	63.70
Professional, Scientific, and Technical Services	0	0	0.088	-0.071	0.020	0.238	5.577	126.222	0	217.01
Administrative and Support Services	-0.001	-0.001	0.095	-0.094	0.025	0.144	4.842	63.857	0	73.70
Waste Management and Remediation Services	0	0	0.151	-0.074	0.021	0.780	10.269	1015.623	0	16.16
Educational Services	0.001	0	0.094	-0.113	0.025	0.0790	4.872	64.834	0	20.33
Ambulatory Health Care Services	-0.001	0	0.125	-0.148	0.026	-0.885	9.427	816.685	0	26.16
Hospitals	0	-0.002	0.231	-0.251	0.045	-0.03	8.297	515.563	0	3.56
Nursing and Residential Care Facilities	-0.003	-0.003	0.420	-0.235	0.053	1.815	22.447	7191.117	0	4.63
Performing Arts, Spectator Sports, and Related Industries	-0.002	-0.003	0.132	-0.113	0.029	0.161	5.473	114.242	0	7.34
Amusement, Gambling, and Recreation Industries	-0.002	-0.002	0.146	-0.111	0.032	0.565	6.439	240.770	0	21.85
Accommodation	-0.002	-0.001	0.234	-0.136	0.043	0.574	6.555	256.529	0	22.66
Food Services and Drinking Places	0	0	0.093	-0.082	0.020	0.169	4.799	61.579	0	62.69
Repair and Maintenance	0	-0.002	0.092	-0.117	0.031	0.219	3.458	7.386	0.025	2.00
Personal and Laundry Services	-0.001	-0.001	0.083	-0.104	0.023	-0.077	5.565	121.363	0	14.32
Finance	-0.001	-0.003	0.149	-0.130	0.035	0.455	6.004	180.977	0	1796.48

Notes: This table presents descriptive statistics of the daily returns for each industry in the crisis period from July 2007 until March 2009, totaling 441 daily observations for each industry.

[a] The average number of firms that are contained in each industry.

Table 9

Descriptive statistics of the dependent and explanatory variables.

	CCX[a]	NET_D_I[b]	VAL_I[c]	INV_I[d]	VOLP[e]	LEV[f]	DEBT_COST[g]	EP[h]	NI[i]	SIZE[j]
Panel A: from January 2001 to December 2011 (3212 observations)										
Mean	1.640	0.008	0.001	0.046	0.027	0.212	0.230	-0.054	-0.002	6.068
Median	0	0.004	0.003	0.011	0.008	0.198	0.214	-0.006	0.004	5.945
Maximum	20	0.269	1.969	24.633	0.480	0.790	0.696	7.675	0.709	9.935
Minimum	0	-0.121	-2.114	-6.221	0	0.023	0.023	-6.238	-0.357	2.726
Std. Dev.	3.192	0.028	0.253	0.952	0.046	0.095	0.116	0.279	0.031	0.984
Panel B: from July 2007 to March 2009 (511 observations)										
Mean	5.511	0.017	-0.170	0.099	0.037	0.217	0.244	-0.112	-0.007	6.216
Median	3	0.012	-0.167	0.010	0.012	0.207	0.229	-0.019	0.001	6.019
Maximum	20	0.218	1.969	24.633	0.479	0.482	0.651	0.113	0.076	9.935
Minimum	0	-0.075	-1.285	-5.122	0	0.038	0.024	-6.238	-0.193	4.067
Std. Dev.	5.461	0.031	0.301	1.599	0.060	0.098	0.121	0.399	0.029	0.919

Notes: This table presents summary statistics for variables employed in Equations (10a) and (10b).

[a] Conditional coexceedance is computed as detailed in Section 3.3.2.
[b] Net debt financing is computed as detailed in Section 3.4.
[c] Spread from a normative value is computed as detailed in Section 3.4.
[d] Spread from a normative investment is computed as detailed in Section 3.4.
[e] Volatility of profitability is computed as detailed in Section 3.4.
[f] Leverage is computed as detailed in Section 3.4.
[g] Industry debt cost is computed as long-term debt divided by the sum of long-term debt and market equity.
[h] Earnings per share.
[i] Net income.
[j] Logarithm of market capitalization.

Table 10

Volatility spillovers.

Industry Name	γ_1 (coef.)	t-stat	γ_2 (coef.)	t-stat	γ_1	γ_2
Crop Production	0.453	2.74	1.210	3.15	*c*	*c*
Animal Production and Aquaculture	0.172	1.15	0.060	0.77		
Forestry and Logging	0.441	3.18	1.182	2.85	*c*	*c*
Oil and Gas Extraction	0.363	3.68	0.380	1.67	*c*	*c*
Mining (except Oil and Gas)	0.292	1.53	0.930	2.55		*c*
Support Activities for Mining	0.642	3.73	0.247	1.09	*c*	
Utilities	0.008	0.11	0.374	2.18		*c*
Construction of Buildings	0.704	2.48	1.242	2.74	*c*	*c*
Heavy and Civil Engineering Construction	0.503	4.43	0.759	3	*c*	*c*
Specialty Trade Contractors	0.493	2.06	0.825	2.15	*c*	*c*
Food Manufacturing	0.122	2.93	0.146	2.15	*c*	*c*
Beverage and Tobacco Product Manufacturing	0.352	5.99	0.006	0.1	*c*	
Textile Mills	0.415	3.48	0.170	1.16	*c*	
Textile Product Mills	0.000	0	1.107	0.55		
Apparel Manufacturing	0.305	4.19	0.616	2.73	*c*	*c*
Leather and Allied Product Manufacturing	0.362	4.45	0.762	3.19	*c*	*c*
Wood Product Manufacturing	0.365	4.18	0.671	2.7	*c*	*c*
Paper Manufacturing	0.218	2.5	0.284	2.43	*c*	*c*
Printing and Related Support Activities	0.225	4.48	0.520	2.59	*c*	*c*
Petroleum and Coal Products Manufacturing	0.271	2.36	0.545	2.4	*c*	*c*
Chemical Manufacturing	0.116	1.76	0.115	1.45	*c*	
Plastics and Rubber Products Manufacturing	0.408	4.97	0.779	3.05	*c*	*c*
Nonmetallic Mineral Product Manufacturing	0.455	2.53	1.023	2.95	*c*	*c*
Primary Metal Manufacturing	0.748	3.01	1.001	2.4	*c*	*c*
Fabricated Metal Product Manufacturing	0.000	0	0.634	2.75		*c*
Machinery Manufacturing	0.272	3.45	0.307	2.02		*c*
Computer and Electronic Product Manufacturing	0.177	3.24	0.236	2.04	*c*	*c*
Electrical Equipment, Appliance, and Component Manufacturing	0.324	4.39	0.380	2.23	*c*	*c*
Transportation Equipment Manufacturing	0.133	1.07	0.439	2.34		*c*
Furniture and Related Product Manufacturing	0.337	4.43	0.852	3.05	*c*	*c*
Miscellaneous Manufacturing	0.182	2.55	0.169	1.77	*c*	*c*
Merchant Wholesalers, Durable Goods	0.276	4.35	0.257	2.18	*c*	*c*
Merchant Wholesalers, Nondurable Goods	0.150	1.88	0.172	1.73	*c*	*c*
Wholesale Electronic Markets and Agents and Brokers	0.091	2.76	0.158	2.75	*c*	*c*
Motor Vehicle and Parts Dealers	0.248	2.11	0.661	2.87	*c*	*c*
Furniture and Home Furnishings Stores	0.000	0	1.131	3.17		*c*
Electronics and Appliance Stores	0.202	0.89	0.211	1.22		
Building Material and Garden Equipment and Supplies Dealers	0.373	4.3	0.744	3.13	*c*	*c*
Food and Beverage Stores	0.280	4.46	0.344	2.82	*c*	*c*
Health and Personal Care Stores	0.313	4.69	0.217	2.32	*c*	*c*
Gasoline Stations	0.800	4.19	0.332	1.53	*c*	
Clothing and Clothing Accessories Stores	0.238	1.56	0.751	2.74		*c*
Sporting Goods, Hobby, Musical Instrument, and Book Stores	0.256	3.74	0.543	2.58	*c*	*c*
General Merchandise Stores	0.149	2	0.403	2.76	*c*	*c*
Miscellaneous Store Retailers	0.523	4.6	0.764	2.99	*c*	*c*
Nonstore Retailers	0.519	3.24	0.348	2.78	*c*	*c*
Air Transportation	2.350	7.33	2.388	2.85	*c*	*c*
Rail Transportation	0.392	4.54	0.565	2.66	*c*	*c*
Water Transportation	0.564	4.47	0.657	2.02	*c*	*c*
Truck Transportation	0.702	4.97	1.043	3.46	*c*	*c*
Pipeline Transportation	0.095	1.27	0.068	0.76		
Support Activities for Transportation	0.582	3.47	0.606	2.57	*c*	*c*
Couriers and Messengers	0.369	5.16	0.249	1.89	*c*	*c*
Warehousing and Storage	0.309	4.27	0.153	1.72	*c*	*c*
Publishing Industries (except Internet)	0.195	4.05	0.260	2.28	*c*	*c*
Motion Picture and Sound Recording Industries	0.262	4.26	0.226	1.95	*c*	*c*
Broadcasting (except Internet)	0.090	0.95	0.340	2.47		*c*
Telecommunications	0.109	1.45	0.312	2.29		*c*
Data Processing, Hosting, and Related Services	0.198	4.32	0.060	0.82	*c*	
Other Information Services	0.226	1.45	0.311	2.15		*c*
Professional, Scientific, and Technical Services	0.057	0.61	0.172	1.7		*c*
Administrative and Support Services	0.237	4.25	0.461	2.72	*c*	*c*
Waste Management and Remediation Services	0.370	4.92	0.259	2.09	*c*	*c*
Educational Services	0.225	3.34	0.296	2.87	*c*	*c*
Ambulatory Health Care Services	0.252	1.62	1.260	3.56		*c*
Hospitals	0.413	4.68	1.267	3.81	*c*	*c*
Nursing and Residential Care Facilities	0.000	0	0.873	2.1		*c*
Performing Arts, Spectator Sports, and Related Industries	0.606	6.42	0.936	3.29	*c*	*c*
Amusement, Gambling, and Recreation Industries	0.815	6.09	0.291	1.28	*c*	
Accommodation	0.792	5.85	0.715	1.65	*c*	*c*
Food Services and Drinking Places	0.227	4.77	0.221	2.09	*c*	*c*
Repair and Maintenance	0.899	4.75	1.081	3.65	*c*	*c*
Personal and Laundry Services	0.172	1.41	0.180	1.32		

Notes: This table presents the results of the volatility spillover by after implementing Equations (1)-(5). We report estimated coefficients of γ_1 and γ_2 (scaled by 1000). The "*c*" stands for spillover during the whole sample and during the crisis period.

Table 11

The likelihoods of CCX.

NAICS3	Prob[a]	$Prob_{crisis}$[b]	$Prob_{non-crisis}$[c]	NAICS3	Prob[a]	$Prob_{crisis}$[b]	$Prob_{non-crisis}$[c]
111	0.0192	0.0726	0.0090	444	0.0235	0.0930	0.0103
112	0.0141	0.0385	0.0095	445	0.0231	0.0726	0.0138
113	0.0289	0.1134	0.0129	446	0.0210	0.0726	0.0112
211	0.0257	0.0794	0.0155	447	0.0231	0.0771	0.0129
212	0.0213	0.0726	0.0116	448	0.0260	0.0952	0.0129
213	0.0242	0.0816	0.0133	451	0.0289	0.0952	0.0163
221	0.0246	0.0884	0.0125	452	0.0199	0.0748	0.0095
236	0.0286	0.1111	0.0129	453	0.0264	0.0930	0.0138
237	0.0253	0.0884	0.0133	454	0.0195	0.0726	0.0095
238	0.0296	0.0998	0.0163	481	0.0249	0.0839	0.0138
311	0.0271	0.0862	0.0159	482	0.0278	0.0907	0.0159
312	0.0224	0.0748	0.0125	483	0.0325	0.1088	0.0181
313	0.0253	0.0771	0.0155	484	0.0235	0.0839	0.0120
314	0.0246	0.0794	0.0142	486	0.0206	0.0680	0.0116
315	0.0314	0.1066	0.0172	488	0.0260	0.0930	0.0133
316	0.0300	0.1066	0.0155	492	0.0275	0.0794	0.0176
321	0.0322	0.1043	0.0185	493	0.0224	0.0703	0.0133
322	0.0322	0.0975	0.0198	511	0.0202	0.0726	0.0103
323	0.0332	0.1202	0.0168	512	0.0300	0.0975	0.0172
324	0.0253	0.0930	0.0125	515	0.0275	0.0794	0.0176
325	0.0289	0.0862	0.0181	517	0.0271	0.0998	0.0133
326	0.0351	0.1088	0.0211	518	0.0278	0.0930	0.0155
327	0.0332	0.1066	0.0193	519	0.0170	0.0544	0.0099
331	0.0300	0.0952	0.0176	541	0.0275	0.0816	0.0172
332	0.0354	0.1202	0.0193	561	0.0354	0.1111	0.0211
333	0.0307	0.0907	0.0193	562	0.0249	0.0816	0.0142
334	0.0192	0.0635	0.0107	611	0.0188	0.0612	0.0107
335	0.0343	0.1066	0.0206	621	0.0206	0.0726	0.0107
336	0.0340	0.1020	0.0211	622	0.0173	0.0726	0.0069
337	0.0325	0.1111	0.0176	623	0.0242	0.0884	0.0120
339	0.0271	0.0816	0.0168	711	0.0282	0.1043	0.0138
423	0.0347	0.1066	0.0211	713	0.0304	0.1043	0.0163
424	0.0296	0.0884	0.0185	721	0.0293	0.1020	0.0155
425	0.0134	0.0408	0.0082	722	0.0253	0.0862	0.0138
441	0.0249	0.0884	0.0129	811	0.0181	0.0703	0.0082
442	0.0224	0.0794	0.0116	812	0.0282	0.0907	0.0163
443	0.0192	0.0703	0.0095				
Average value of all industries							
	0.0261	0.0875	0.0144				
		Difference†	0.0730†				
		P-value‡	<0.0001‡				

Notes: The NAICS3 indicates the three-digit code of NAICS.

[a] The likelihood of CCX over the whole sample period.
b The likelihood of CCX during the crisis period (from July 2007 to March 2009).
c The likelihood of CCX during the non-crisis period.
† The average difference between $Prob_{crisis}$ and $Prob_{non-crisis}$.
‡ One-sided p-value of the Wilcoxon two-sample test.

Table 12

The likelihoods of CCX: Competitive and concentrated industries.

Year	Prob[a]	$Prob_{cometitive}$[b]	$Prob_{concentrated}$[c]	Difference[†]	P-value[‡]
2001	0.0163	0.0177	0.0141	0.0036 *	0.0674
2002	0.0160	0.0168	0.0146	0.0022	0.1447
2003	0.0186	0.0192	0.0190	0.0002	0.4807
2004	0.0175	0.0201	0.0154	0.0047 **	0.0139
2005	0.0142	0.0141	0.0132	0.0009	0.2393
2006	0.0203	0.0210	0.0190	0.0020	0.2307
2007	0.0299	0.0297	0.0294	0.0003	0.3791
2008	0.0329	0.0358	0.0329	0.0029 *	0.0821
2009	0.0269	0.0300	0.0256	0.0044 **	0.0156
2010	0.0328	0.0351	0.0328	0.0023 *	0.0998
2011	0.0331	0.0340	0.0313	0.0027 *	0.0971
Total sample	0.0235	0.0248	0.0225	0.0023 ***	0.0092

Notes: We identify competitive industries as those for which the fitted HHI is in the lowest 25% and concentrated industries as those in the highest 25%. For each year, the sample contains 73 industries, 18 of which belong to competitive industries and 18 of which are concentrated industries.

[a] The average yearly likelihood of CCX for all industries.
b The average yearly likelihood of CCX for competitive industries.
b The average yearly likelihood of CCX for concentrated industries.
† The average difference between $Prob_{competitive}$ and $Prob_{concentrated}$.
‡ One-sided p-value of the Wilcoxon two-sample test.
* Significance level at 10%.
** Significance level at 5%.
*** Significance level at 1%

Table 13

CCX: The impact of industry characteristics.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.[a]	EI[b]	Coef.[a]	EI[b]	Coef.[a]	EI[b]	Coef.[a]	EI[b]	Coef.[a]	EI[b]
NET_D_I			2.842***	8.52%					2.567***	7.67%
			(3.25)						(3.06)	
VAL_I					-0.623***	-14.67%			-0.618***	-14.56%
					(-6.37)				(-6.32)	
INV_I							-0.071***	-6.59%	-0.056***	-5.23%
							(-4.01)		(-2.90)	
VOLP	1.984***	9.97%	1.858***	9.31%	2.09***	10.53%	1.97***	9.89%	1.934***	9.70%
	(5.28)		(4.77)		(5.71)		(5.24)		(5.06)	
Debt_Cost	0.706***	8.62%	0.669***	8.15%	0.588***	7.13%	0.706***	8.62%	0.56***	6.78%
	(3.33)		(3.18)		(2.78)		(3.33)		(2.65)	
EP	-0.155***	-4.30%	-0.155***	-4.30%	-0.119***	-3.32%	-0.156***	-4.32%	-0.121***	-3.37%
	(-3.36)		(-3.40)		(-2.76)		(-3.40)		(-2.87)	
SIZE	-0.114***	-10.71%	-0.12***	-11.24%	-0.095***	-9.01%	-0.114***	-10.71%	-0.103***	-9.73%
	(-3.37)		(-3.51)		(-2.84)		(-3.39)		(-3.03)	
cons	-0.065		-0.052		-0.159		-0.054		-0.131	
	(-0.34)		(-0.27)		(-0.83)		(-0.28)		(-0.68)	
Time effect	YES		YES		YES		YES		YES	
Industry effect	YES		YES		YES		YES		YES	
Number of group	73		73		73		73		73	
Number of observations	3212		3212		3212		3212		3212	
Wald test null: all coefficients=0	0†		0†		0†		0†		0†	
Pseudo-R^2	0.3951		0.3976		0.4105		0.3965		0.4145	

Notes: Estimation results are obtained by using GMM with instrumental variables of the baseline balanced Poisson panel regressions, see Equation (10a). The dependent variable is the conditional coexceedance of the real economy industries. Independent variables are defined in Table 9. The sample spans from 1Q2001 to 4Q2011. All independent variables are lagged one quarter. The numbers in parentheses are t-statistics adjusted for clustering at the industry level.

[a] The estimated coefficient of regressions.
b Economic impact, which is computed as detailed in Footnote 43 of the main text.
† The p-value of the Wald test.
* Significance level at 10%.
** Significance level at 5%.
*** Significance level at 1%.

Table 14

CCX: The impact of industry characteristics in crisis and non-crisis periods.

	Model 1		Model 2		Model 3	
	Coef.[a]	EI[b]	Coef.[a]	EI[b]	Coef.[a]	EI[b]
NET_D_I*non-crisis dummy	1.855 *	4.87%				
	(1.91)					
NET_D_I*crisis dummy	3.066 **	4.46%				
	(2.50)					
NET_D_I			2.54 ***	7.58%	2.571 ***	7.68%
			(3.06)		(3.07)	
VAL_I*non-crisis dummy			-0.572 ***	-11.84%		
			(-5.77)			
VAL_I*crisis dummy			-0.67 ***	-7.99%		
			(-3.94)			
VAL_I	-0.614 ***	-14.48%			-0.62 ***	-14.61%
	(-6.26)				(-6.34)	
INV_I*non-crisis dummy					-0.079 **	-5.48%
					(-2.36)	
INV_I*crisis dummy					-0.049 **	-3.10%
					(-2.11)	
INV_I	-0.056 ***	-5.23%	-0.055 ***	-5.14%		
	(-2.86)		(-2.76)			
VOLP	1.922 ***	9.64%	1.905 ***	9.55%	1.94 ***	9.74%
	(4.99)		(4.74)		(5.07)	
Debt_Cost	0.561 ***	6.79%	0.569 ***	6.89%	0.558 ***	6.75%
	(2.66)		(2.70)		(2.64)	
EP	-0.12 ***	-3.34%	-0.118 ***	-3.29%	-0.121 ***	-3.37%
	(-2.85)		(-2.77)		(-2.86)	
SIZE	-0.102 ***	-9.64%	-0.103 ***	-9.73%	-0.103 ***	-9.73%
	(-3.01)		(-3.05)		(-3.03)	
Cons	-0.123		-0.125		-0.127	
	(-0.64)		(-0.66)		(-0.66)	
Time effect	YES		YES		YES	
Industry effect	YES		YES		YES	
Number of group	73		73		73	
Number of observations	3212		3212		3212	
Wald test null: all coefficients=0	0†		0†		0†	
Pseudo-R^2	0.4178		0.4229		0.4148	

Notes: We obtained estimation results using GMM with instrumental variables of the baseline balanced Poisson panel regressions as shown in Equation (10b). The dependent variable is the CCX of the real economy industries. Independent variables are defined in Table 9. The sample spans from 1Q2001 to 4Q2011. We split our three main industry variables into two variables: the first variable represents industry variable times non-crisis dummy, which equals one before the third quarter of 2007 and after the first quarter of 2009 and zero otherwise, and the second variable represents industry variable times crisis dummy, which equals one between the third quarter of 2007 and the first quarter of 2009 and zero otherwise. The numbers in parentheses are t-statistics adjusted for clustering at the industry level.

a The estimated coefficient of regressions.
b Economic impact, which is computed as detailed in Footnote 43 in the main text.
† The p-value of the Wald test.
* Significance level at 10%.
** Significance level at 5%.
*** Significance level at 1%.

Table 15

CCX: The impact of industry characteristics in competitive and concentrated industries

	Model 1		Model 2		Model 3		Model 4	
	Coef.[a]	EI[b]	Coef.[a]	EI[b]	Coef.[a]	EI[b]	Coef.[a]	EI[b]
Panel A: Estimation results for competitive industries (792 observations)								
NET_D_I*non-crisis dummy			2.765					
			(1.09)					
NET_D_I*crisis dummy			6.085*	6.53%				
			(1.78)					
NET_D_I	4.798**	12.63%			4.768*	12.54%	4.748 *	12.49%
	(2.00)				(1.97)		(1.99)	
VAL_I*non-crisis dummy					-0.812***	-15.04%		
					(-4.42)			
VAL_I*crisis dummy					-0.834***	-7.66%		
					(-2.68)			
VAL_I	-0.82***	-16.74%	-0.806***	-16.48%			-0.82 ***	-16.74%
	(-4.81)		(-4.74)				(-4.82)	
INV_I*non-crisis dummy							-0.152 ***	-11.22%
							(-2.84)	
INV_I*crisis dummy							-0.052	
							(-0.32)	
INV_I	-0.112		-0.113		-0.112			
	(-1.61)		(-1.64)		(-1.61)			
Pseudo R^2	0.438		0.448		0.457		0.438	
Panel B: Estimation results for concentrated industries (792 observations)								
NET_D_I*non-crisis dummy			0.013					
			(0.01)					
NET_D_I*crisis dummy			2.531					
			(1.16)					
NET_D_I	1.867				1.886		1.848	
	(1.08)				(1.09)		(1.07)	
VAL_I*non-crisis dummy					-0.580***	-12.45%		
					(-3.12)			
VAL_I*crisis dummy					-0.739*	-10.72%		
					(-1.90)			
VAL_I	-0.674***	-17.14%	-0.672***	-17.09%			-0.668 ***	-17.00%
	(-2.74)		(-2.70)				(-2.64)	
INV_I*non-crisis dummy							0.079	
							(0.50)	
INV_I*crisis dummy							0.032	
							(0.33)	
INV_I	0.042		0.045		0.052			
	(0.50)		(0.53)		(0.50)			
Pseudo R^2	0.429		0.431		0.441		0.431	

Notes: We obtained estimation results using GMM with instrumental variables of the baseline balanced Poisson panel regressions as shown in Equations (10a) and (10b). The dependent variable is the CCX of the real economy industries. Independent variables are defined in Table 9. The sample contains only competitive industries, from the first quarter of 2001 to the fourth quarter of 2011. We split our three main industry variables into two variables: the first variable represents industry variable times non-crisis dummy, which equals one before the third quarter of 2007 and after the first quarter of 2009 and zero otherwise, and the second variable represents industry variable times crisis dummy, which equals one between the third quarter of 2007 and the first quarter of 2009 and zero otherwise. The numbers in brackets are t-statistics adjusted for clustering at the industry level. All models include control variables, industry dummy, and time dummy as used in Table 13 and 14. To save space, we do not report these results here.

[a] The estimated coefficient of regressions.
[b] Economic impact, which is computed as detailed in Footnote 43 in the main text.
† The *p*-value of the Wald test.
* Significance level at 10%.
** Significance level at 5%.
*** Significance level at 1%.

Table 16

Tail risk spillover using DD.

Variables	Model 1	Model 2
$DD_{fin}{}^{a}$*non-crisis dummy		1.508 ***
		(13.71)
DD_{fina}* crisis dummy		1.693 ***
		(14.08)
$DD_{fin}{}^{a}$	1.508 ***	
	(13.71)	
VOLP	-0.227	-0.227
	(-1.14)	(-1.14)
LEV	-4.671 ***	-4.671 ***
	(-17.35)	(-17.35)
EP	0.066 **	0.066 **
	(2.23)	(2.23)
SIZE	0.098 ***	0.098 ***
	(3.28)	(3.28)
Time effect	YES	YES
Industry effect	YES	YES
Number of groups	73	73
Number of observations	3139	3139
R-squared	0.6238	0.6238

Notes: Estimation results are for the baseline balanced panel regressions. The dependent variable is the DD values for 73 industries. Our sample spans from second quarter 2001 to fourth quarter 2011. We estimate the coefficients by means of a Prais-Winsten robust to heteroskedasticity, contemporaneous correlation across panels. The table first presents the estimated coefficients and then in parentheses the t-statistics adjusted for clustering at the industry level.

[a] The DD value of financial sector
** Significance level at 5%.
*** Significance level at 1%.

Table 17. Descriptive statistics across countries and regions: 2003–2011

This table reports the summary statistics on CCX and independent variables across 16 European countries and four regions. The definition of regions is as follows: Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain), Euro-core countries (Austria, Germany, France, the Netherlands, Finland, Belgium), major non-euro zone countries, except for UK (Sweden, Norway, Denmark, Switzerland), and UK.

Country	Country code	Obs.	Percent of observations	Number of firms		*CCX*	*vol*	*dd*	*logmb*	*ret*	*cashmta*	*size*	*tlmta*
Panel A: Summary statistics on CCX and independent variables for each country													
Austria	AUT	1585	1.54%	62		0.625	0.456	5.308	0.224	0.026	0.09	6.034	0.537
Belgium	BEL	2545	2.47%	94		0.679	0.389	7.348	0.401	0.018	0.089	5.915	0.484
Switzerland	CHE	4076	3.95%	156		0.752	0.372	8.316	0.48	0.021	0.098	6.244	0.39
Germany	DEU	14112	13.68%	561		0.604	0.503	5.445	0.346	0.026	0.094	5.489	0.506
Denmark	DNK	2852	2.76%	111		0.629	0.487	6.302	0.551	0.014	0.087	4.895	0.411
Spain	ESP	3139	3.04%	115		0.922	0.319	8.069	0.586	0.012	0.06	6.913	0.477
Finland	FIN	3397	3.29%	118		0.617	0.419	6.378	0.494	0.020	0.081	5.378	0.436
France	FRA	16018	15.52%	615		0.662	0.45	6.289	0.446	0.017	0.097	5.403	0.504
United Kingdom	GBR	29023	28.13%	1356		0.547	0.446	6.663	0.523	0.008	0.076	5.063	0.433
Greece	GRC	5174	5.01%	199		0.925	0.498	3.069	-0.179	-0.024	0.055	5.438	0.624
Ireland	IRL	1169	1.13%	50		0.503	0.514	5.989	0.452	0.007	0.105	5.987	0.446
Italy	ITA	6022	5.84%	237		0.949	0.347	6.306	0.342	-0.012	0.08	6.224	0.546
Netherlands	NLD	3052	2.96%	131		0.810	0.401	6.857	0.574	0.023	0.065	6.47	0.462
Norway	NOR	3646	3.53%	179		0.768	0.598	4.630	0.832	0.012	0.069	5.228	0.418
Portugal	PRT	1388	1.35%	48		0.646	0.396	5.053	0.294	-0.003	0.043	6.509	0.659
Sweden	SWE	5991	5.81%	288		0.699	0.519	5.769	0.578	0.016	0.071	4.686	0.412
Panel B: Summary statistics on CCX and independent variables across different regions													
Euro-periphery countries		16892	16.37%	649	Mean	0.881	0.403	5.517	0.232	-0.009	0.067	6.118	0.559
{PRT, IRL, ITA, GRC, ESP}					Std	1.712	0.208	4.847	0.888	0.185	0.066	1.571	0.224
Euro-core countries		40709	39.45%	1581	Mean	0.649	0.458	6.074	0.414	0.021	0.092	5.567	0.496
{AUT. DEU, FRA, NLD, BEL, FIN}					Std	1.559	0.262	4.386	0.779	0.186	0.083	1.865	0.219
Major non-euro zone countries, except for UK		16565	16.05%	734	Mean	0.715	0.495	6.237	0.605	0.016	0.08	5.225	0.408
{SWE, NOR, DNK, CHE}					Std	1.643	0.307	4.714	0.893	0.202	0.079	1.759	0.223
United Kingdom (UK)		29023	28.13%	1356	Mean	0.547	0.446	6.663	0.523	0.008	0.076	5.063	0.433
					Std	1.323	0.273	5.037	0.916	0.215	0.077	2.02	0.213
Panel C: Summary statistics on CCX and independent variables for the whole sample													
Total		103189	100%	4320	Mean	0.669	0.452	6.175	0.445	0.012	0.081	5.461	0.474
					Std	1.541	0.267	4.72	0.864	0.197	0.079	1.884	0.225

Table 18. Descriptive statistics across regions and time periods

This table reports the summary statistics on CCX across different areas and time periods in Panel A. The testing of differences on CCX between any two areas for a given time period is presented in Panel B. In Panel B, bold fonts stand for the difference between a pair of CCX across two regions is significant at more than 5% level.

Panel A: Summary statistics of CCX across different areas and time periods				
Region\Period	Full sample	Stable	Crisis_07_09	Crisis_EU
Euro-periphery	0.881	0.326	1.793	1.421
(number of observations)	(16892)	(9606)	(3748)	(3538)
Euro-core	0.649	0.264	1.546	0.845
(number of observations)	(40709)	(24254)	(8685)	(7770)
Non-Euro (exclude UK)	0.715	0.303	1.809	0.716
(number of observations)	(16565)	(9551)	(3599)	(3415)
UK	0.547	0.189	1.533	0.617
(number of observations)	(29023)	(18105)	(6231)	(4687)
Panel B: Test the differences on CCXs between two different areas for a given time period				
Region\Period	Full sample	Stable	Crisis_07_09	Crisis_EU
Euro-periphery versus Euro-core	**0.232**	**0.062**	**0.246**	**0.575**
Euro-periphery versus Non-Euro (exclude UK)	**0.165**	**0.023**	**-0.016**	**0.705**
Euro-periphery versus UK	**0.334**	**0.137**	**0.260**	**0.804**
Euro-core versus Non-Euro (exclude UK)	**-0.067**	**-0.039**	**-0.262**	0.130
Euro-core versus UK	**0.101**	**0.075**	**0.013**	**0.228**
Non-Euro (exclude UK) versus UK	**0.168**	**0.114**	0.275	**0.099**

Table 19. Firms' characteristics and CCX

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within different regions. Dependent variable is quarterly CCX. Explanatory variables are: Volatility (vol), Distance to Default (dd), Growth opportunity (logmb), Past Quarterly Return (ret), Cash Holding (cashmta), Firm size (logsize), and Leverage (tlmta). All regressions include firm fixed effects and control for business cycle. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. E.I. (%) stands for "Economic Impact at percentage".

	Full sample	E. I. (%)	Euro-periphery	E. I. (%)	Euro-core	E. I. (%)	Non-Euro	E. I. (%)	UK	E. I. (%)
Model	(1)		(2)		(3)		(4)		(5)	
vol_{t-1}	1.076 ***	33.22	0.722 ***	16.23	1.405 ***	44.59	0.997 ***	35.80	0.883 ***	27.26
	[0.035]		[0.102]		[0.056]		[0.081]		[0.062]	
dd_{t-1}	-0.009 ***	-3.98	-0.021 ***	-9.57	-0.008		-0.006		-0.001	
	[0.003]		[0.007]		[0.005]		[0.006]		[0.005]	
$logmb_{t-1}$	-0.071 ***	-5.99	-0.045		-0.083 ***	-6.26	-0.100 **	-8.58	-0.095 ***	-8.34
	[0.018]		[0.038]		[0.031]		[0.044]		[0.030]	
ret_{t-1}	-0.730 ***	-13.42	-0.710 ***	-12.29	-0.529 ***	-9.39	-0.851 ***	-15.80	-0.917 ***	-17.93
	[0.032]		[0.073]		[0.053]		[0.084]		[0.059]	
$cashmta_{t-1}$	-0.633 ***	-4.87	-0.419		-0.626 ***	-5.09	-0.680 *	-5.22	-0.873 ***	-6.48
	[0.145]		[0.364]		[0.208]		[0.352]		[0.278]	
$logsize_{t-1}$	0.090 ***	18.48	0.035		-0.004		0.068 ***	12.73	0.365 ***	109.07
	[0.024]		[0.048]		[0.040]		[0.047]		[0.043]	
$tlmta_{t-1}$	0.709 ***	17.30	1.113 ***	28.30	0.666 ***	15.74	0.414 **	9.69	0.400 ***	8.90
	[0.083]		[0.210]		[0.137]		[0.188]		[0.148]	
Control Business cycle (GDP)	Yes		Yes		Yes		Yes		Yes	
Time dummy	Yes		Yes		Yes		Yes		Yes	
Number of observations	103189		16892		40709		16565		29023	
Log pseudolikelihood	-90656		-17041		-35878		-15890		-20228	

Table 20. Cashing holding and CCX during the 07-09 financial crisis

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within different regions. Dependent variable is quarterly CCX. Crisis_07_09 is an indicator variable equal to one for calendar quarters between July 2007 and March 2009. Crisis_07_09 dummy x cashmta is interaction term. All explanatory variables are defined in Table 19. All regressions include firm fixed effects and control for business cycle. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

	Full sample		Periphery		Core		Non-euro-zone (no UK)		UK	
Model	(1)		(2)		(3)		(4)		(5)	
$cashmta_{t-1}$	-0.428	***	-0.494		-0.278		-0.847	**	-0.446	
	[0.159]		[0.392]		[0.221]		[0.384]		[0.321]	
crisis_07_09 dummy	1.129	***	0.743	***	1.243	***	0.993	***	1.398	***
	[0.024]		[0.047]		[0.041]		[0.059]		[0.041]	
crisis_07_09 dummy x $cashmta_{t-1}$	-0.296	**	0.307		-0.618	***	0.542		-0.626	**
	[0.151]		[0.368]		[0.221]		[0.367]		[0.276]	
vol_{t-1}	0.715	***	0.429	***	0.987	***	0.687	***	0.509	***
	[0.035]		[0.106]		[0.057]		[0.081]		[0.062]	
dd_{t-1}	-0.022	***	-0.027	***	-0.024	***	-0.019	***	-0.014	***
	[0.003]		[0.007]		[0.005]		[0.006]		[0.005]	
$logmb_{t-1}$	-0.095	***	-0.058		-0.110	***	-0.116	***	-0.126	***
	[0.018]		[0.039]		[0.032]		[0.045]		[0.031]	
ret_{t-1}	-0.279	***	-0.355	***	-0.068		-0.439	***	-0.396	***
	[0.034]		[0.075]		[0.057]		[0.086]		[0.063]	
$logsize_{t-1}$	0.010		-0.025		-0.064		0.009		0.202	***
	[0.024]		[0.050]		[0.039]		[0.048]		[0.042]	
$tlmta_{t-1}$	0.876	***	1.314	***	0.779	***	0.589	***	0.573	***
	[0.084]		[0.220]		[0.140]		[0.189]		[0.148]	
Control Business cycle (GDP)	Yes		Yes		Yes		Yes		Yes	
Time dummy	Yes		Yes		Yes		Yes		Yes	
Number of observations	103189		16892		40709		16565		29023	
Log pseudolikelihood	-88772		-16845		-35144		-15631		-19438	

Table 21. **Financial constraint: CCX across different periods and regions**

Numbers in the table are the average values of CCX across all three financially constrained criteria. The 'C' stands for financially constrained firms and 'U' for financially unconstrained firms. We report the average values across different regions and across different time period. Bold face fonts present numbers of (U-C)/C.

	2003-2011		Stable		Crisis_07_09		Crisis_EU	
	C	U	C	U	C	U	C	U
All countries	0.550	0.816	0.229	0.296	1.319	2.040	0.714	1.091
	0.527		**0.329**		**0.588**		**0.603**	
Euro-periphery	0.785	1.014	0.304	0.362	1.603	2.036	1.240	1.678
	0.319		**0.219**		**0.287**		**0.401**	
Euro-core	0.541	0.770	0.239	0.293	1.272	1.893	0.687	1.046
	0.458		**0.252**		**0.521**		**0.600**	
Non-Euro (exclude UK)	0.598	0.846	0.268	0.343	1.537	2.185	0.573	0.909
	0.446		**0.308**		**0.454**		**0.656**	
UK	0.396	0.748	0.153	0.238	1.089	2.172	0.457	0.857
	1.006		**0.640**		**1.130**		**1.018**	

Table 22. Financial constraint: Descriptive statistics on cash holding across regions

This table presents the ratio of a firm's cash holding to its total asset in 16 European countries across financially constrained firms (C) and financially unconstrained firms (U) based on three alternative criteria (Firm size, firm age, and payout ratio). We report the values of means and medians for each category. Bold face fonts indicate the cases that financially constrained firms have lower cash holding than unconstrained firms.

		Financial constraint criteria					
		Firm size		Firm age		Payout ratio	
		C	U	C	U	C	U
All countries	Mean	0.089	0.074	0.089	0.073	0.085	0.073
	Median	0.058	0.052	0.060	0.050	0.056	0.051
	Std	0.087	0.069	0.085	0.071	0.082	0.069
Euro-periphery	Mean	**0.064**	**0.071**	0.067	0.065	**0.063**	**0.068**
	Median	**0.040**	**0.052**	**0.044**	**0.046**	**0.044**	**0.049**
	Std	0.067	0.064	0.067	0.062	0.060	0.064
Euro-core	Mean	0.103	0.080	0.106	0.079	0.096	0.084
	Median	0.072	0.059	0.077	0.055	0.067	0.061
	Std	0.093	0.071	0.091	0.074	0.088	0.075
Non-Euro (exclude UK)	Mean	0.087	0.073	**0.078**	**0.080**	0.084	0.072
	Median	0.055	0.050	**0.048**	**0.055**	0.053	0.050
	Std	0.087	0.069	0.082	0.074	0.084	0.068
UK	Mean	0.085	0.066	0.086	0.066	0.079	0.059
	Median	0.057	0.045	0.056	0.045	0.053	0.041
	Std	0.085	0.066	0.084	0.067	0.079	0.059

Table 23. Financial constraints, cash holdings, and CCX during the 07-09 financial crisis

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within 16 European countries. Dependent variable is quarterly CCX. For three measures of financial constrains (firm size, firm age, payout ratio), the subsamples comprises firms with financial constraint measures below and above the sample median. Crisis is an indicator variable equal to one for calendar quarters between July 2007 and March 2009. Crisis x cashmta is interaction term. All variables are defined in Table 19. All regressions include firm fixed effects and control for business cycle. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

	Firm size				Firm age				Payout ratio			
	C		U		C		U		C		U	
$cashmta_{t-1}$	-0.051		-0.798	***	-0.133		-0.857	***	-0.272		-0.519	*
	[0.230]		[0.227]		[0.231]		[0.234]		[0.241]		[0.282]	
crisis	1.229	***	1.081	***	1.158	***	1.121	***	1.139	***	1.149	***
	[0.041]		[0.030]		[0.039]		[0.031]		[0.039]		[0.035]	
crisis x $cashmta_{t-1}$	-0.390	*	-0.301		-0.415	*	-0.043		-0.706	***	-0.232	
	[0.232]		[0.205]		[0.214]		[0.220]		[0.245]		[0.259]	
vol_{t-1}	0.614	***	0.761	***	0.697	***	0.739	***	0.753	***	0.716	***
	[0.053]		[0.051]		[0.052]		[0.054]		[0.054]		[0.066]	
dd_{t-1}	-0.017	***	-0.022	***	-0.010	***	-0.024	***	-0.008		-0.026	***
	[0.005]		[0.004]		[0.005]		[0.004]		[0.005]		[0.004]	
$logmb_{t-1}$	-0.067	**	-0.123	***	-0.120	***	-0.107	***	-0.140	***	-0.101	***
	[0.027]		[0.027]		[0.027]		[0.027]		[0.028]		[0.037]	
ret_{t-1}	-0.143	***	-0.317	***	-0.194	***	-0.245	***	-0.220	***	-0.219	***
	[0.050]		[0.046]		[0.051]		[0.048]		[0.051]		[0.057]	
$logsize_{t-1}$	0.053		0.030		0.039		-0.027		0.005		-0.093	*
	[0.038]		[0.036]		[0.036]		[0.040]		[0.035]		[0.050]	
$tlmta_{t-1}$	0.981	***	0.938	***	0.924	***	0.925	***	0.782	***	1.479	***
	[0.123]		[0.127]		[0.126]		[0.127]		[0.132]		[0.156]	
gdp	-0.199		-0.430	***	-0.519	**	-0.383	**	-0.434	**	0.013	
	[0.216]		[0.147]		[0.203]		[0.152]		[0.213]		[0.190]	
Firm-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Time dummy	Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	50401		51217		47257		48224		41583		41062	
Log pseudolikelihood	-33776		-53355		-36911		-45967		-34521		-38423	

Table 24. Financial constraints, cash holdings, and CCX during the 07-09 financial crisis across different areas

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within 16 European countries. Dependent variable is quarterly CCX. For three measures of financial constrains (firm size, firm age, payout ratio), the subsamples comprises firms with financial constraint measures below and above the sample median. Crisis is an indicator variable equal to one for calendar quarters between July 2007 and March 2009. All regressions include firm-level controls (vol, dd, logmb, ret, logsize, tlmta), gdp per capital is used to control for business cycles, firm-fixed effects, time dummy. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

	Firm size		Firm age		Payout ratio	
Panel A: Within Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain)						
	C	U	C	U	C	U
$cashmta_{t-1}$	0.150	-1.143 **	-0.117	-1.143	-0.453	-0.529
	[0.611]	[0.546]	[0.586]	[0.546]	[0.719]	[0.575]
crisis	0.846 ***	0.678 ***	0.753 ***	0.678 ***	0.691 ***	0.832 ***
	[0.068]	[0.064]	[0.071	[0.064]	[0.081]	[0.072]
crisis x $cashmta_{t-1}$	0.388	0.473	0.390	0.473	-0.008	0.143
	[0.590]	[0.475]	[0.524]	[0.475]	[0.747]	[0.576]
Number of observations	8218	8418	7693	7715	6719	6900
Log pseudolikelihood	-6989	-9577	-7100	-8356	-6674	-6968
Panel B: Within Euro-core countries (Austria, Germany, France, the Netherlands, Finland, Belgium)						
	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	0.083	-0.653 **	-0.057	-0.569 *	-0.258	-0.309
	[0.320]	[0.311]	[0.308]	[0.332]	[0.315]	[0.385]
crisis	1.439 ***	1.140 ***	1.298 ***	1.219 ***	1.341 ***	1.188 ***
	[0.071]	[0.051]	[0.065]	[0.056]	[0.064]	[0.059]
crisis x $cashmta_{t-1}$	-0.977 ***	-0.511	-0.901 ***	-0.307	-1.199 ***	-0.154
	[0.334]	[0.316]	[0.294]	[0.355]	[0.347]	[0.349]
Number of observations	20061	20162	19227	18907	17960	17168
Log pseudolikelihood	-13614	-20889	-15619	-17491	-14348	-15863
Panel C: Within major non-euro zone countries, except for UK (Sweden, Norway, Denmark, Switzerland)						
	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	-0.206	-1.276 **	-0.640	-1.253 **	-0.454	-1.289 *
	[0.587]	[0.547]	[0.596]	[0.527]	[0.610]	[0.761]
crisis	1.089 ***	0.980 ***	1.072 ***	0.969 ***	1.089 ***	0.954 ***
	[0.104]	[0.074]	[0.098]	[0.080]	[0.101]	[0.088]
crisis x $cashmta_{t-1}$	0.608	0.222	0.706	0.799 *	0.198	0.569
	[0.535]	[0.472]	[0.610]	[0.455]	[0.578]	[0.662]
Number of observations	8067	8237	7315	8064	6918	6650
Log pseudolikelihood	-5947	-9332	-6196	-8384	-6179	-6561
Panel D: Within UK						
	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	-0.213	-0.748 *	0.182	-1.244 **	0.048	-1.142 *
	[0.484]	[0.452]	[0.479]	[0.496]	[0.506]	[0.666]
crisis	1.566 ***	1.329 ***	1.480 ***	1.340 ***	1.335 ***	1.429 ***
	[0.079]	[0.050]	[0.079]	[0.051]	[0.071]	[0.060]
crisis x $cashmta_{t-1}$	-1.115 **	-0.431	-0.911 **	-0.044	-0.866 **	-0.336
	[0.514]	[0.358]	[0.364]	[0.450]	[0.431]	[0.615]
Number of observations	14055	14400	13022	13538	9986	10344
Log pseudolikelihood	-6555	-12509	-7242	-10769	-6622	-8321

Table 25. Financial constraints, cash holdings, and CCX during the 07-09 and EU debt crisis

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within 16 European countries. Dependent variable is quarterly CCX. For three measures of financial constrains (firm size, firm age, payout ratio), the subsamples comprises firms with financial constraint measures below and above the sample median. Crisis is an indicator variable equal to one for calendar quarters from July 2007 to March 2009 (Global crisis) and from May 2010 to December 2011 (EU crisis). Crisis x cashmta is interaction term. All variables are defined in Table 19. All regressions include firm fixed effects and control for business cycle. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

	Firm size				Firm age				Payout ratio			
	C		U		C		U		C		U	
cashmta$_{t-1}$	0.164		-0.665	**	0.256		-0.877	***	-0.096		-0.358	
	[0.265]		[0.263]		[0.268]		[0.266]		[0.277]		[0.322]	
crisis	1.185	***	1.085	***	1.153	***	1.108	***	1.096	***	1.154	***
	[0.043]		[0.031]		[0.041]		[0.033]		[0.040]		[0.035]	
crisis x cashmta$_{t-1}$	-0.576	**	-0.363		-0.819	***	0.008		-0.686	**	-0.375	
	[0.248]		[0.234]		[0.233]		[0.250]		[0.270]		[0.278]	
vol$_{t-1}$	0.620	***	0.745	***	0.701	***	0.722	***	0.756	***	0.694	***
	[0.052]		[0.050]		[0.052]		[0.053]		[0.053]		[0.065]	
dd$_{t-1}$	-0.019	***	-0.025	***	-0.012	***	-0.028	***	-0.009	*	-0.030	***
	[0.005]	`	[0.004]		[0.005]		[0.004]		[0.005]		[0.004]	
logmb$_{t-1}$	-0.061	**	-0.115	***	-0.110	***	-0.103	***	-0.129	***	-0.098	***
	[0.027]		[0.027]		[0.027]		[0.027]		[0.027]		[0.037]	
ret$_{t-1}$	-0.174	***	-0.317	***	-0.216	***	-0.251	***	-0.244	***	-0.218	***
	[0.050]		[0.045]		[0.050]		[0.048]		[0.051]		[0.057]	
logsize$_{t-1}$	0.060		0.033		0.043		-0.024		0.012		-0.091	*
	[0.038]		[0.036]		[0.035]		[0.040]		[0.035]		[0.050]	
tlmta$_{t-1}$	0.956	***	0.916	***	0.911	***	0.887	***	0.771	***	1.427	***
	[0.123]		[0.127]		[0.126]		[0.127]		[0.133]		[0.157]	
gdp	-0.189		-0.425	***	-0.532	***	-0.369	**	-0.422	**	0.026	
	[0.216]		[0.147]		[0.202]		[0.153]		[0.213]		[0.189]	
Firm-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Time dummy	Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	50401		51217		47257		48224		41583		41062	
Log pseudolikelihood	-33708		-53102		-36812		-45753		-34424		-38241	

Table 26. Financial constraints, cash holdings, and CCX during the 07-09 and EU debt crisis across different areas

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within 16 European countries. Dependent variable is quarterly CCX. For three measures of financial constrains (firm size, firm age, payout ratio), the subsamples comprises firms with financial constraint measures below and above the sample median. Crisis is an indicator variable equal to one for calendar quarters from July 2007 to March 2009 (Global crisis) and from May 2010 to December 2011 (EU crisis). All regressions include firm-level controls (vol, dd, logmb, ret, logsize, tlmta), gdp per capital is used to control for business cycles, firm-fixed effects, time dummy. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: Within Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain)

	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	0.663	-1.219 **	0.825	-1.461 **	-0.200	-0.174
	[0.815]	[0.573]	[0.670]	[0.576]	[0.886]	[0.668]
crisis	0.715 ***	0.549 ***	0.644 ***	0.582 ***	0.543 ***	0.714 ***
	[0.079]	[0.064]	[0.076]	[0.064]	[0.084]	[0.069]
crisis x $cashmta_{t-1}$	-0.654	0.249	-1.076 *	0.806	-0.424	-0.520
	[0.736]	[0.499]	[0.577]	[0.516]	[0.854]	[0.587]
Number of observations	8218	8418	7693	7715	6719	6900
Log pseudolikelihood	-7004	-9584	-7117	-8355	-6687	-6976

Panel B: Within Euro-core countries (Austria, Germany, France, the Netherlands, Finland, Belgium)

	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	0.083	-0.653 **	-0.057	-0.569 *	-0.258	-0.309
	[0.320]	[0.311]	[0.308]	[0.332]	[0.315]	[0.385]
crisis	1.439 ***	1.140 ***	1.298 ***	1.219 ***	1.341 ***	1.188 ***
	[0.071]	[0.051]	[0.065]	[0.056]	[0.064]	[0.059]
crisis x $cashmta_{t-1}$	-0.977 ***	-0.511	-0.901 ***	-0.307	-1.199 ***	-0.154
	[0.334]	[0.316]	[0.294]	[0.355]	[0.347]	[0.349]
Number of observations	20061	20162	19227	18907	17960	17168
Log pseudolikelihood	-13549	-20776	-15541	-17397	-14281	-15773

Panel C: Within major non-euro zone countries, except for UK (Sweden, Norway, Denmark, Switzerland)

	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	-0.206	-1.276 **	-0.640	-1.253 **	-0.454	-1.289 *
	[0.587]	[0.547]	[0.596]	[0.527]	[0.610]	[0.761]
crisis	1.089 ***	0.980 ***	1.072 ***	0.969 ***	1.089 ***	0.954 ***
	[0.104]	[0.074]	[0.098]	[0.080]	[0.101]	[0.088]
crisis x $cashmta_{t-1}$	0.608	0.222	0.706	0.799 *	0.198	0.569
	[0.535]	[0.472]	[0.610]	[0.455]	[0.578]	[0.662]
Number of observations	8067	8237	7315	8064	6918	6650
Log pseudolikelihood	-5909	-9245	-6148	-8312	-6130	-6504

Panel D: Within UK

	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	-0.213	-0.748 *	0.182	-1.244 **	0.048	-1.142 *
	[0.484]	[0.452]	[0.479]	[0.496]	[0.506]	[0.666]
crisis	1.566 ***	1.329 ***	1.480 ***	1.340 ***	1.335 ***	1.429 ***
	[0.079]	[0.050]	[0.079]	[0.051]	[0.071]	[0.060]
crisis x $cashmta_{t-1}$	-1.115 **	-0.431	-0.911 **	-0.044	-0.866 **	-0.336
	[0.514]	[0.358]	[0.364]	[0.450]	[0.431]	[0.615]
Number of observations	14055	14400	13022	13538	9986	10344
Log pseudolikelihood	-6552	-12407	-7217	-10689	-6591	-8250

Table 27. Financial constraints (identified before crisis), cash holdings, and CCX during the 07-09 financial crisis.

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within 16 European countries. Dependent variable is quarterly CCX. For three measures of financial constrains (firm size, firm age, payout ratio), the subsamples comprises firms with financial constraint measures below and above the sample median. Crisis is an indicator variable equal to one for calendar quarters between July 2007 and March 2009. Crisis x cashmta is interaction term. All variables are defined in Table 19. All regressions include firm fixed effects and control for business cycle. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

	Firm size		Firm age		Payout ratio	
	C	U	C	U	C	U
$cashmta_{t-1}$	-0.065	-0.754 ***	0.013	-0.835 ***	-0.279	-0.455 *
	[0.240]	[0.242]	[0.255]	[0.242]	[0.253]	[0.263]
crisis	1.203 ***	1.110 ***	1.187 ***	1.103 ***	1.154 ***	1.129 ***
	[0.043]	[0.031]	[0.039]	[0.033]	[0.042]	[0.034]
crisis x $cashmta_{t-1}$	-0.782 ***	-0.268	-1.012 ***	0.147	-0.729 ***	-0.226
	[0.250]	[0.218]	[0.237]	[0.230]	[0.256]	[0.233]
vol_{t-1}	0.634 ***	0.818 ***	0.676 ***	0.794 ***	0.827 ***	0.742 ***
	[0.058]	[0.055]	[0.057]	[0.056]	[0.058]	[0.062]
dd_{t-1}	-0.022 ***	-0.026 ***	-0.017 ***	-0.029 ***	-0.019 ***	-0.027 ***
	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
$logmb_{t-1}$	-0.074 ***	-0.112 ***	-0.127 ***	-0.092 ***	-0.108 ***	-0.084 **
	[0.028]	[0.028]	[0.029]	[0.028]	[0.028]	[0.033]
ret_{t-1}	-0.180 ***	-0.209 ***	-0.154 ***	-0.237 ***	-0.163 ***	-0.207 ***
	[0.058]	[0.047]	[0.055]	[0.052]	[0.054]	[0.056]
$logsize_{t-1}$	0.021	-0.039	0.002	-0.012	-0.013	-0.039
	[0.033]	[0.039]	[0.036]	[0.039]	[0.035]	[0.045]
$tlmta_{t-1}$	0.783 ***	0.880 ***	0.784 ***	0.866 ***	0.642 ***	1.088 ***
	[0.125]	[0.129]	[0.131]	[0.130]	[0.133]	[0.141]
gdp	-0.461 **	-0.657 ***	-0.711 ***	-0.463 ***	-0.393 *	-0.527 ***
	[0.229]	[0.154]	[0.203]	[0.166]	[0.206]	[0.181]
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	40744	46376	38332	44698	37194	39304
Log pseudolikelihood	-28408	-47322	-31175	-41324	-30857	-37897

Table 28. Financial constraints (identified before crisis), cash holdings, and CCX during the 07-09 financial crisis across different areas

This table presents estimates from Panel Poisson regressions explaining firm-level quarterly CCX within 16 European countries. Dependent variable is quarterly CCX. For three measures of financial constrains (firm size, firm age, payout ratio), the subsamples comprises firms with financial constraint measures below and above the sample median. Crisis is an indicator variable equal to one for calendar quarters from July 2007 to March 2009 (Global crisis) and from May 2010 to December 2011 (EU crisis). Crisis x cashmta is interaction term. All variables are defined in Table 4. All regressions include firm fixed effects and control for business cycle. Standard errors (in brackets) are heteroskedasticity-consistent and clustered by firm. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Panel A: Within Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain)

	Firm size				Firm age				Payout ratio			
	C		U		C		U		C		U	
$cashmta_{t-1}$	0.141		-0.563		0.148		-0.964		-0.530		-0.297	
	[0.576]		[0.571]		[0.608]		[0.599]		[0.680]		[0.605]	
crisis	0.826	***	0.711	***	0.803	***	0.687	***	0.819	***	0.710	***
	[0.075]		[0.067]		[0.071]		[0.072]		[0.084]		[0.067]	
crisis x $cashmta_{t-1}$	-0.527		0.362		-0.763		0.738		-0.373		0.331	
	[0.732]		[0.482]		[0.679]		[0.524]		[0.762]		[0.511]	
Number of observations	6976		7503		6736		6630		6247		6513	
Log pseudolikelihood	-6135		-8150		-6648		-6754		-6098		-6968	

Panel B: Within Euro-core countries (Austria, Germany, France, the Netherlands, Finland, Belgium)

	Firm size				Firm age				Payout ratio			
	C		U		C		U		C		U	
$cashmta_{t-1}$	0.052		-0.697	**	-0.067		-0.524		-0.088		-0.439	
	[0.333]		[0.333]		[0.351]		[0.330]		[0.338]		[0.353]	
crisis	1.425	***	1.155	***	1.285	***	1.209	***	1.340	***	1.181	***
	[0.074]		[0.054]		[0.072]		[0.056]		[0.071]		[0.058]	
crisis x $cashmta_{t-1}$	-1.000	***	-0.476		-0.823	**	-0.259		-1.146	***	-0.079	
	[0.348]		[0.344]		[0.330]		[0.346]		[0.365]		[0.329]	
Number of observations	16706		18579		15044		18679		16188		16730	
Log pseudolikelihood	-11684		-18943		-12492		-16902		-12738		-16015	

Panel C: Within major non-euro zone countries, except for UK (Sweden, Norway, Denmark, Switzerland)

	Firm size				Firm age				Payout ratio			
	C		U		C		U		C		U	
$cashmta_{t-1}$	-0.496		-1.432	**	-0.352		-1.556	***	-0.840		-0.759	
	[0.623]		[0.589]		[0.684]		[0.535]		[0.588]		[0.723]	
crisis	1.056	***	0.988	***	1.068	***	0.963	***	1.053	***	0.989	***
	[0.116]		[0.080]		[0.104]		[0.083]		[0.112]		[0.087]	
crisis x $cashmta_{t-1}$	0.022		0.471		-0.332		0.991	**	0.144		0.544	
	[0.599]		[0.512]		[0.639]		[0.496]		[0.571]		[0.649]	
Number of observations	6022		7046		5308		7165		5804		6258	
Log pseudolikelihood	-4890		-7919		-4913		-7392		-5492		-6375	

Panel D: Within UK

	Firm size				Firm age				Payout ratio			
	C		U		C		U		C		U	
$cashmta_{t-1}$	0.106		-0.748		0.623		-1.017	*	0.151		-1.066	*
	[0.580]		[0.482]		[0.531]		[0.534]		[0.535]		[0.597]	
crisis	1.553	***	1.361	***	1.515	***	1.332	***	1.371	***	1.410	***
	[0.084]		[0.050]		[0.070]		[0.056]		[0.074]		[0.061]	
crisis x $cashmta_{t-1}$	-1.515	***	-0.279		-1.770	***	0.142		-0.845	*	-0.436	
	[0.575]		[0.381]		[0.430]		[0.496]		[0.460]		[0.608]	
Number of observations	11040		13248		11244		12224		8955		9803	
Log pseudolikelihood	-5078		-11304		-6439		-9385		-5866		-8003	